# SOFT COMPUTATION BASED INDIAN TOPOGRAPHIC MAP UNDERSTANDING SYSTEM (ITMUS)

**Ph.D. THESIS**

*by*

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**A THESIS**

***Submitted in partial fulfilment of the requirements for the award of the degree***

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## CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in this thesis entitled "**Soft Computation Based Indian Topographic Map Understanding System (ITMUS)"** in partial fulfillment of the requirements for the award of the Degree of Doctor of Philosophy and submitted in the Department of Civil Engineering, Indian Institute of Technology Roorkee, Roorkee is an authentic record of my own work carried out at Department of Civil Engineering during the period from July 2010 to June 2016 under the supervision of Dr. Jayanta Kumar Ghosh, Associate Professor, Department of Civil Engineering, Indian Institute of Technology Roorkee, Roorkee, India.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other Institute.

**(Nikam Gitanjali Ganpatrao)**

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

**(Jayanta Kumar Ghosh)**
Supervisor

The Ph.D. Viva-Voce Examination of **Nikam Gitanjali Ganpatrao**, Research Scholar, has been held on **20.09.2016** at **9:30 am**.

**Chairman, SRC** **Signature of External Examiner**

This is to certify that the student has made all the corrections in the thesis.

**Signature of Supervisor** **Head of the Department**

**Dated:20.09.2016**

# ABSTRACT

A topographic map is an important source of information for geospatial planning and analysis. Apart from conventional uses, nowadays topographic maps have been extensively used for the development of automated Geo-information system including GIS and decision support system. These mostly rely on the topographic map to obtain geographic information, location details, the extent of urban area and landscape analysis, etc. The information of interest to any geospatial application requires being extracted from topographic maps. At present, extraction of information is being carried out through manual digitization or semiautomated methods which require expertise and human intervention. Also, these approaches are slow and error prone. Hence, there is great need to automate extraction of information from the topographic map.

Few systems have been developed for the interpretation of topographic map, but the approaches are insufficient to automatically extract geospatial information and are incapable of understanding the topographic map. The research work as done so far not lead to a precise formulation of the map objects description and classification. Most of the map interpretation systems emphasize particular coherent organization of maps or raster to vector conversion process. To provide a solution for the manual digitization and to access the topographic map information efficiently, sophisticated approaches for semi-automatic selective map interpretation have been reported by many researchers. The proposed approaches yield good recognition rates for the well-isolated objects of interests. Few existing systems have dealt with the problems of recognition of limited map objects, but most of them have confined the scope of research for linear object's reconstruction and recognition. Most of the systems have not considered extraction of geospatial information.

The topographic maps are quite complex. Complexity is due to color ambiguity, spatial ambiguity and pattern indiscrimination present in the topographic map. Existing approaches have not provided any robust framework for handling color information and pattern indiscriminate present in a topographic map. However, the human map reader is excellent in pattern recognition. Hence, the topographic map understanding approach must be more natural to conceive based on the humanistic approach rather than recognizing edges, object boundaries and syntactic arrangement of structure primitives. Hence, a generalized framework has been needed to handle the high variability of graphical content displayed on the topographic map. Data or information capturing by a human is quite efficient. But human understanding may get bias due to inconsistencies. In contrast, computers are more deliberate and less prone to error. Hence, the research work has been visualized by the concept of

integration of human and computer map processing towards the automated understanding the topographic map.

The main objective of this research work is to develop an automated system for the understanding of Survey of India (SOI) topographic map. To achieve the objective of topographic map understanding the human mentation and learning capabilities have been emulated by computer treatment to develop a soft computation based Indian Topographic Map understanding system (ITMUS). The first phase in human map understanding process is reading of map legends which uses color and geometrical appearance of legend. The Legend understanding subsystem (LUS) has been devised to represent the legend numerically and described using a set of shape and structure parameters as well as color which has been used at a different level of matching. The LUS performs static rule based matching and legend recognition, which is consisting of structure and shape parameters in premise part and semantic description of the legend in consequent part in a hierarchical manner. The LUS has been tested on legend set developed by Survey of India and obtained an average accuracy of 88.424%. The interpreted legend description data set has been partitioned into training set libraries based on the data model prepared by Modern Cartographic Center, Survey of India. The second phase in human map reading is to utilize the legend description data for interpreting the objects/symbols present on a topographic map. This phase has been emulated by the Map understanding subsystem (MUS) which uses legend description data to acquire information about the legend. However, topographic map treatment by the computer system is not easy due to high density and overlapping of map objects. This situation has been dealt with, a “peeling onion strategy”, where the continuous subtraction of the already recognized map layers has been carried out using image processing techniques to simplify the processing of the rest of the complex layers. For map object interpretation, "correlation theory of brain" has been employed. It has been done by designing Fuzzy Inference System (FIS) to infer rules from initial training set libraries. Once the initial membership functions have been created, the training of system has been carried out by providing legend structure data and membership function created by FIS. After the training of system has been finished, the final membership functions and training error have been produced. The checking data have been used along with training data to make a system understand and interpret the topographic map objects. The output of ITMUS effectively conveys the interpreted information to end user. A map understanding which has been derived from MUS is represented in the form of an interpreted map (i-map) along with geo-location information. The i-map representation deals with presenting the annotated/labeled topographic map objects inside the ROI which has been selected by the end user. The ITMUS generates thematic map information in .tiff, .xlsx, .txt and .tab form. The thematic map layer contains geometrical and geospatial information. The ITMUS stores interpretation results of legends set in excel worksheet and in .pdf file format. The map analysis report includes the semantic meaning of the interpreting object, it's geometrical feature values, pixel location, pixel list, and geo-coordinates. ITMUS also provides insight to the user to extract the color based, feature based layers as well as intermediate description. The ITMUS has incorporated with an inbuilt accuracy assessment, a utility for both symbol and layer extraction assessments. Thus, the developed system provides a generalized framework for automated topographic map understanding by contributing automated geolocation based information extraction and retrospective map analysis for further computer-based information processing.

The system performance has been evaluated by providing testing data set into the fuzzy system through the selection of a region of interest from topographic map. These data structure consists of a shape feature description of map objects present in that region. The output of ITMUS represents the semantic description code and provides a resultant understanding about the map object. The semantic code has been measured on the basis of correlations between the desired context and learning content. To evaluate and validate ITMUS with respect to different outputs, different case studies have been carried out to test different parameters. The ITMUS has been trained for various sample regions selected from the Survey of India Topographic maps having identity contains, 53C7 and 53K1 under OSM category. To carry out an evaluation of the system, different map regions have been selected from 53C7, 53F6, 53F7, 53F11, and 53K1.

It has been found that the overall recognition rate of the system is 90.91%. Further, the system has been assessed on three other different criteria, i.e., its overall completeness, correctness, and rate of correct recognition. The criteria have been found to be 0.93, 0.99 and 93.79% respectively. A measure of the overall classification accuracy derived is 88.235%. The accuracy assessment and validation of ITMUS shows that system is highly robust and reliable as it is doing well for testing and checking topographic map region. Thus, it may be concluded that an ITMUS has successfully been developed. The major contribution of this research work is the integration of image processing techniques for feature extraction and reasoning capabilities of the Neuro-fuzzy model for enriching the Indian topographic information system. The major outcome of the study is the development of a generalized human based map understanding framework for automated extraction of information from the topographic map. The comprehensive conceptual formalism of map understanding and development of a robust and reliable solution for automated acquisition and extraction of information from the Indian topographic map has been made possible.

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Indian Institute of Technology (Nikam Gitanjali Ganpatrao)
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# Abbreviations

Most of the symbols are defined as they occur in the thesis. Some of the most common symbols, which are used repeatedly, are listed below.

| | |
|---|---|
| ANFIS | Adaptive Neuro-Fuzzy System |
| ANN | Artificial Neural Network |
| AUC | Area Under Curve |
| BPANN | Back Propagation Artificial Neural Network |
| DEM | Digital Elevation Model |
| DSN | Data Set Number |
| DRG | Digital Raster Graphics |
| DTC | Decision Tree Classifier |
| EXT | Extracted Object |
| FCM | Fuzzy C-Means |
| FIS | Fuzzy Interference System |
| FL | Fuzzy Logic |
| FN | False Negative |
| FP | False Positive |
| FPR | False Positive Rate |
| FRP | False Positive Rate |
| GeoTIFF | Georeferenced Tagged Image File Format |
| HSI | Hue-Saturation-Intensity |
| GIS | Geographic Information System |
| ITMUS | Indian Topographic Map Understanding System |
| LSE | Least Square Estimator |
| LU | Legend Understanding |
| LUS | Legend Understanding Subsystem |
| MAP | Mean Average Precision |
| MF | Membership Function |
| MSE | Mean Square Error |
| MU | Map Understanding |
| MUS | Map Understanding Subsystem |
| OCR | Optical Character Recognition |
| OSM | Open Series Map |

| | |
|---|---|
| PO | Post Office |
| PROLOG | Procedural Logic Programming Language |
| PROMAP | Processing of Map |
| REF | Referenced |
| RGB | Red-Green-Blue color space |
| RMSE | Root Mean Square Error |
| ROC | Receiver Operating Characteristics |
| ROI | Region of Interest |
| RS | Random Selection |
| SOI | Survey of India |
| TIFF | Tagged Image File Format |
| TP | True Position |
| TPR | Time Positive Rate |
| TR | Training Samples |
| TRP | Time Positive Rate |
| TS | Testing Samples |
| USGC/USGS | United States Global Change /United states geological survey |
| UTM | Universal Transverse Mercator |
| WGS | World Geodetic System |

# CHAPTER 1 INTRODUCTION

## 1.1 INTRODUCTION

A topographic map is an important tool for geospatial planning and analysis. It is the basic source of information for all activities requiring Geospatial information. It is primarily used in applications like urban area planning and development [45, 282], disaster management, settlement of legal boundaries and land administration (e.g. Cadastral map) etc. Apart from conventional uses, nowadays topographic maps have been extensively used for the development of automated Geo-information system including GIS. Consequently, geospatial information technologies, mostly rely on the topographic map to obtain geographic information, location details, the extent of urban area and landscape analysis, etc. The information of interest for any geospatial application requires being extracted from topographic maps. Also, development of a spatial decision support system has been highly constrained by automating information extraction from topographic map. The spatial decision support system (SDSS) is making use of geographical data, database management system and user interface to assist analysis of decision-making [324]. Geospatial information system and technology (GIST) uses the spatial and nonspatial information to make evidence-based decision-making [49, 214], also makes use of digital spatial data for assessment of causative factors of landslide [43, 44]. For Geospatial Information Technology (GIT), the geospatial information is required for natural resources and agriculture management [207, 229, 305]. The web mapping services with eligible spatial data layers have been applied to the applications in urban planning activities [45]. Geospatial data support decision making in transportation infrastructure [126]. Thus, geospatial data is the basis for planning, management and development. Hence, extracting geospatial data and making them available to the Decision Support System (DSS) and the automated geospatial system automatically is an important task. For various applications of GIS, it has been necessary to recognize and understand different objects in a map as a collection of layers. In addition to solving geospatial information extraction, automated map understanding may find many applications such as data acquisition, map generalization [345], spatial datasets matching [316], data fusion [18, 328] or data update [43, 317] etc. The insistent and peremptory demand for spatial data/information is to increase, which requires the extraction of information automatically. Therefore, it is an increasing scope to automate the extraction of information from topographic map through automated map understanding method.

At present, numerous topographic maps are made digitally available through national mapping agency. Scanning topographic map and digital topographic map developed by the 'Survey of India' (SOI) provides a digital storage library of topographic maps, but it is not in a computer accessible or understandable format [223]. The DRG is Georeferenced raster image of a map which is disseminated or publishing before printing it on paper. Such digital map has been suitable for display or rendering purposes as the information encoded in the map is in raster based or pixel-based form. This information conveys geographical, geospatial, topological information about map objects but cannot be accessed directly for computer processing or computer based geospatial system. The computer cannot analyze such an information or knowledge presented on the topographic map directly. The burden of providing this knowledge falls mostly on the supplier of the map which usually follows a human based process. The process is being carried out mostly through interactive digitization, which is done either manually or in the semi-automated way [84, 182]. For example, Survey of India is preparing open series topographic maps with the help of a human operator who is responsible for augumenting a semantic description and geographical and spatial information to a digital map entity. They follow cartographic conventions to store geometrical information about a map entity [215]. This process is time-consuming and highly laborious. Therefore, there is exigent requirement to develop a robust and reliable automated system to understand and extract the information from topographic map automatically and annotate map objects as well. Here, robust means highly accurate and complete system, which is able to extract and interpret the same type of map object when applied to different series of topographic maps. While reliability stands for the how well the system performs the tasks for which it has been intended.

In the next section, the motivation behind the development of topographic map understanding has been discussed. Also, a brief review of the existing study and motivation of the research work in the context of human and machine understanding have been described. The objectives have been outlined in section 1.3. Understanding the Indian topographic map to facilitate information extraction and object interpretation using a human based approach has been proposed in section 1.4. The proposed strategy has been put in perceptive of soft computation in contemporary topographic map understanding the framework. In section1.5, the organization of the thesis is provided.

## 1.2 MOTIVATION

For several of geospatial activities, it has been necessary to understand different objects/symbols on a map as a collection of layers. However, the information or data, in the topographic map are no longer directly accessible in the computer. The main difficulty lies in topographic map understanding is due to highly dense map objects [190]. The pattern indeterminacy is present in the topographic map which is due to intrinsic vague and random topography. In the map, same geographical object exhibits different patterns at various locations according to ground reality. Few systems have been developed for the interpretation of topographic map, but the systems cannot work properly and failed to produce geospatial and geographic information from topographic map [3-5, 20, 36, 51, 72]. The algorithms have to deal with varying object representations as well as coalesced and blurred objects. The indefiniteness in map object's pattern may be explained in terms of color ambiguity or geometrical structure ambiguity or both. Color ambiguity means indefiniteness of deciding a pixel or Spatial uncertainty refers to indefiniteness in geometry. Hence, object recognition methods must be more natural to conceive object pattern based on the features like color and geometry rather than recognizing edges, object boundaries and syntactic arrangement of structure primitives. The most of the research work [88, 152, 218] does not lend to a precise formulation of feature descriptors. Some of the map interpretation systems emphasize simply coherent organization of maps, raster to vector conversion process [62, 89, 254]. Some of the work uses a similarity measure to determine the mismatch between recognized objects and original object by superimposing on each other [254]. However, the distance measure is insufficient to distinguish between true or false matches. Also noisy map objects would not produce good recognition result. Some of the researchers adopted color key and line tracing algorithm for contour lines from scanned topographic map samples, but the remaining symbols or objects stayed unrecognized. Frame-based modeling for image interpretation of topographic map has been used by few researchers. The efficiency of the realizing semantic net has not been proved for the acquisition of all map entities. Hudra et al. [157] fused raster-to-vector conversion to neural network model for enhancing recognition of the building and parcel, but the scope of this system has been limited to the cadastral map only. Some researchers [5] applied binarization, vectorization and digitization to detect structural representation, but the system has been under operator control. The researchers have chosen approaches which are not performing in natural and morphological way to read a topographic map. They have devised methods which are unrelated to the human based topographic map reading and understanding.

Many sophisticated approaches for semi-automatic, selective or complete map interpretation have been reported by many researchers [5, 14, 68, 99, 104, 183, 204, 241, 273, 332]. The proposed approaches yield good recognition rates for the well-isolated objects of interests, but performance has been limited to a single and small size map layout. The developed approaches require manual intervention and lack the incorporation of spatial information in map interpretation. The very few existing system has dealt with the problems of recognition of limited map objects, but most of them have confined the scope of research for reconstruction and recognition of linear objects [75, 173, 206, 269, 271, 272]. Most of the system which has been discussed above have not considered geospatial information extraction and have limited scope to interpret linear or well-isolated map symbols. The most of the research work has been based on the preset objective which is limited to specific map objects. Ebi [89] have worked on topographic maps and devised knowledge acquisition method based on truth maintenance system. However, this approach has been inefficient for complex topographic map as the use of certain features and lack of method to find correlation between structure primitives. Some researchers have emphasized very simple and limited number of objects in the form of homogeneous and constituent segments with the color information and shape attributes [71, 160]. In literature, query based map information retrieval has been existing but requires some sort of expertise and human intervention. The query-based information retrieval has been limited for only a few objects of topographic maps. In their approach, they have suggested that the highly complex nature of topographic maps and interconnected or overlapped map objects would not be easy to make the computer understand map without any manual intervention [152, 154, 332]. But, writing down hundreds of computer programs, specialized in recognizing specific map object and recognition under human control is not a good choice. However, the generalized framework has not been developed yet due to the high variability of graphical content displayed on the topographic map.

The map making agencies like 'Survey of India' (in India) make use of digitizer to convert paper-based topographic map in digital form and vector map data gets created and maintained using manual tagging for further applications. So, there is also a need for automatic understanding and automatic tagging of a raster map. As discussed earlier, the topographic map has been often reported in a paper or in digital form. However, the raster representation comprising of pixel details are often insufficient to provide geographical or geospatial information directly to the computer for map analysis. Hence, automating topographic/spatial information extraction from the digital topographic map is one of the greatest need. In order to make use of the potential of a topographic/spatial data and to extract spatial information in layers, an automatic map understanding system is required. Hence, research has been highly motivated by the need of the generalized map understanding approach rather than relying on complex pattern recognition algorithms.

There are two ways to extract information from the topographic map. One is human based and other is machine based, each having its own advantages and weaknesses. Reading a map either by human or, by machine using correct level of meta-knowledge for any aspect to be interpreted usually leads to correct understanding result. Human interprets the highly complex topographic map quite easily based on learned map legends. However, legend based human map reading or conventional topographic map reading has not been addressed till. In human based map understanding emulation process, it has been necessary to understand the human analytical way and human mentation functions to read map [230]. In conventional map reading, human first reads and understands the topographic map legends and then the derived knowledge (which may include color, shape, etc.) is used to gain the semantic meaning of the objects/symbols presented on a topographic map. Semantic meaning of the map object may be defined by mapping the low-level visual features by high-level concept description [279]. This is the analytical way in which human reader interacts with a topographic map, however, the biological way in which human understands topographic map information is based on human mentation and correlation theory. Human map reader is able to understand the variation of the same map object depicted at different locations on the map. The human reader is able to infer a decision in a partially occluded situation also. So, it is clear that human thinking is not based on crisp boundaries but considers fuzziness. Thus, partial visibility can be dealt by human and completing the task with ease but no machine can perform it without the use of fuzzy systems. The human is able to learn and adapt new information. The appearance of the legend is sufficiently different from those objects present in the actual map. Still, the human reader is able to recognize it and adapt it for further reading. In the existing research works, researchers have disdained human-based model and have not considered natural mentation and analytical model of map reading. Recently, many works have been started to model the indefiniteness or uncertainty. But, it gains very little attention in the area of map interpretation or understanding. The main limitation of human map understanding is that it is not always consistent. Also, manual extraction of map layer has been a tedious, slow and expensive process. On the other hand, computers have been more deliberate, more precise and less prone to exhaustion and error than the human map reader. Hence, the computer treatment of digital topographic map to emulate human map understanding ability to recognize pattern and to select most relevant map object may proven to be most perplexing task.

Preliminary to map understanding process, the map legends should be accurately studied and decomposed into its different components, ordering their shape characteristics and inventorying relations between it and their corresponding semantic meaning. The humanistic process involves eye's physiological function, the transformation of light reflected from objects into neural signals and thought process which are carried out by neurons. The result of thought processing is the understanding of the legends or map object. The human understanding may use two vital processes to separate map objects from the background: a process that uses local methods which segregate borders of adjacent regions and a global method that assimilate similar objects. The global similarity process contributes to image segmentation by color. A fundamental goal is to discover, distinguish, and identify objects. But before interpreting maps, it has been necessary to determine which parts of the object can be held together. This process is termed as map segmentation, fundamental to both human and machine. Usually, the object is discriminated from other objects or from the background based on object variations on their boundaries and object persistence within boundaries. Moller and Hurlbert [216] have derived two theories of human visual segmentation and description which exploit fundamental distinctions based on the shape which uses 1) local edge-based process that marks differences in image gradient attributes, and 2) global region-based process that finds the congruent area by combining statistical information about attributes over space [216, 342]. Human also considers collective and essential characteristic objects to understand map object. Thus, human interpretation of topographic map consists of a process which instantiates local/global attributes that may be integrated recursively into a more complex object descriptor.

Simulation of human map reading ability to recognize topographic map objects and to select relevant data with respective understanding using machine can be taken up in different ways. Hence, a hybrid approach combining feature knowledge and soft computing approach may be an appealing technique to handle and learn vague and variability of topographic map effectively for the automatic understanding of topographic maps. However, soft computational methods have been used for satellite images, but in map document analysis or understanding this technique has not been explored yet. Thus, development of an automated system emulating the humanistic learning and understanding of legends and map may be visualized as a solution to the problem of understanding and extracting geospatial information from the topographic map.

So, there is a great need for a humanistic approach which is capable of automating information extraction from topographic map. Hence, comprehensive conceptual formalism and development of human based robust and reliable map understanding system for information acquisition, extraction and understanding have been the main motivation of the research work.

## 1.3 OBJECTIVE OF THE RESEARCH

The main objective of the present research work is to develop an Indian topographic map understanding system**.** The sub-objective is to develop an Indian Topographic map legend understanding subsystem.

In this thesis, two issues are mainly investigated in the development of a legend based topographic map understanding: first, description of object using geometrical features and second, soft computational methods for the interpretation. Here, idea is to create a generalized framework for measuring features of all topographic map object to retrieve object description from a series of topographic maps and apply a learning based classification in order derive semantic descriptions associated with the map object.

## 1.4 PROPOSED STRATEGY

Map understanding problem may be approached by image preprocessing, computer vision, computational intelligence, mathematics, and optimization. In this study, the use of the potential of a feature based and learning based approach to topographic map analysis needs to be investigated and employed. Also, the idea is to handle uncertainty at a high level of vision algorithm. As discussed earlier, uncertainty arises due to topographic map's density and complexity. To deal with this problem, a “peel onion approach” [81] may be useful where the map layers would be subtracted into the different layers, making the task simple in order to facilitate the understanding of more compound layers. This is logically equivalent to reverse cartography [175]. Feature-based classification may be helpful in order to retrieve map objects based on categories from a multi-temporal series of topographic maps. This category wise specification of the topographic map has been provided in Data model for digital cartography which is prepared by the Modern Cartographic Center, Survey of India [215]. The color is the most dominant and distinguishing feature in the topographic map and hence it may be useful or even necessary to develop a color-coding mechanism to perform gross classification of topographic objects and landforms in different layers. The layer separation framework may be provided by the combined work of the color coding methods and gap filling methods. This intersection and overlapping conditions could be handled to some extent. The shape feature may be appealing for dealing with pattern recognition. Description of map object by considering this aspect is again important in the psychological characteristics in recognizing objects in the map. In the topographic map, overlapping or intersection disrupts map object and their boundaries. Also, the topographic map object appearance has been fixed for compact cell type symbol, but the appearance of linear object varies from one location to another. Therefore, a set of morphological image processing techniques may be attempted for fragile representative feature description which has an important consideration into recognition and understanding. An ideal model of map understanding system should classify an unknown input pattern into one of a set of pre-specified classes. The task must be divided into a hierarchical strategy for recognition of classes. Hence, a hierarchical approach may be employed to instantiate topographic map into a framework for better understanding such as from object instances to semantics/concept and from simple to more complex layers. However, the basic idea is that the whole problem of understanding should be driven by a humanistic approach which uses legend information. The system may generate a set of rules for the legend data. The important issues in the development of map understanding system are the development of interfaces, which includes graphical tools for referring to parts of a topographic map and interact with map and map databases for maintaining geometrical and geospatial information of the map object. Also, the true capability of the topographic map understanding system may not extend until the achievement of automated learning techniques for feature description and recognition strategies. Hence the exploration of such techniques to provide generalized and robust computation platform for all kinds of topographic map symbols is the proposed strategy**.**

The following are the broad steps in research strategy: (a) developing principle methods for integration of multiple understanding modalities relies on the map object description, and leading to machine understanding capabilities; (b) Methods for separating map images into constituent layers from multiple perspective for improved topographic map analysis; (c) developing methods for storing extracted geospatial information in map spatial analysis report based on content for storage and retrieval; (d) locating objects and inferring the semantic description of objects; (e) developing a reliable map understanding system that integrate low-level image processing with high-level reasoning. These include the need of investigating good representations, and description schemes or a hybrid method of representation.

Thus, the combination of human map reading and machine computation capabilities may provide a better solution to automated topographic map understanding and extraction of geospatial layer information. In confronting automated topographic map understanding the problem, an implementation of a complementary hybrid system that recognizes map legend patterns and adapts itself to cope with the varying nature of topographic map; inference systems that incorporate initial knowledge of topographic map legend set and perform learning is needed. So, soft computation based topographic map understanding may be a generalized solution providing a humanistic approach in the hybrid intelligent system to reason and learn in an environment of vague and imprecise nature of topographic maps.

## 1.5 ORGANIZATION OF THE THESIS

In the present chapter, a general introduction along with the objective and scope of the present investigation is described. The remaining contents of the thesis are organized in the following manner.

**Chapter 2** gives a review of the literature related to the map understanding and interpretation system. In this, the advantages and limitations of the existing systems have been discussed. Furthermore, the extent of scope for development has been discussed. Principal problems in the research area, achievements and relevant methods corresponding to this area have been outlined and further scope of research has been identified.

**Chapter 3** provides the technologies and their background theories which have been used to form a good platform for creating an automated map understanding system.

**Chapter 4** proposes the Indian Topographic Map understanding system (ITMUS); its design, architecture, and development. Further, the flow of control within the system has been explained.

**Chapter 5** provides the implementation and working details of the proposed system. The input data set and ANFIS parameter setting has been described.

**Chapter 6** illustrates the ITMUS working and validation as well as generalization capacity has been discussed.

**Chapter 7** summarizes the development of the system concisely. It also summarizes the contributions of the research work and future scope in this area for research.

# CHAPTER 2 LITERATURE REVIEW

## 2.1 INTRODUCTION

The topographic map provides a configuration of landscape objects and ground entities using different map symbols. Reading a topographic map using key or legend means getting semantic meaning associated with each map symbol which is depicted on a map. Understanding map is a process which uses some basic assumptions on the kind of entity encoded in the map. So for every kind of aspect to be interpreted in the map, it has been sensible to understand the basic assumptions on the ground entity and meta-knowledge regarding map symbols. Reading a map using correct level of meta-knowledge for any aspect of the entity to be interpreted, usually leads to correct interpretation results. To provide a geoinformation based system a complete understanding of topographic maps and geospatial thematic layer's knowledge automatically has been challenging task. Also, development of a spatial decision support system based on geographical data has been a high constraint by automating information extraction from topographic map. Traditional uses of the topographic map include navigation and terrain modeling, for which a geospatial knowledge component of the system will become necessary since information needs to be understood based on the extracted map object. But automation in the spatial information extraction and understanding of raster topographic map to locate and understand geographic entity by a computer system has not been trivial to achieve because the wide variety of the landscape objects, the complexity of heavily interconnected geographical elements and labels, and overlapping of different objects in maps [83, 88]. The objective of the chapter is to review the important works done for an understanding of maps typically topographic map. The work done for different document understanding domain has also been studied.

The chapter has been organized as follows. Section 2.2 outlines brief discussion on map understanding methods and in further sub-sections it classifies existing methods in different categories based on some basic principle factors that have been chosen to review existing work in map understanding domain. Further, section 2.3 gives a brief discussion of existing map understanding systems and their comparative evaluation. Section 2.4 concludes with the principal problems in the research area, achievements and relevant methods and scope of research.

## 2.2 MAP UNDERSTANDING METHODS

Map understanding is a process of understanding geographical entity, spatial pattern, and semantic relationships. The aim of map understanding is to recognize the pattern of map objects represented by the symbols like Village/Town, roads, rivers and regions on a map and acquire relevant semantic information which has been specified in legend set. The map understanding process supports geospatial data acquisition. The map making agencies like Survey of India (in India) make use of digitizer to convert the paper-based map into digital raster graphics, which further maintained through binding a semantic meaning with map objects by manual tagging. It has been potentially huge, complicated and labor intensive task. Also, for topographic map generalization, map updates, and many such tasks rely on the information content on a topographic map. Manual information extraction or pattern selection is a slow process [190], which should be as automated. However, the work done in topographic map understanding or interpretation domain is less frequent in the literature. In the section below, an attempt is made to divide the existing works in the map as well as image understanding domain into several classes and categories.

### 2.2.1 Comprehensive Classification

The surveys of different techniques of the automatic and semi-automatic map or image interpretation methods have been classified based on the variety of existing proposals in the literature. The work done so far in the domain of the map or image understanding have been studied in accordance with the principal factors. These factors include the objective, the type of Map entities to be interpreted, the interpretation technique applied, the sequential steps utilized for interpretation. The classification of literature based on these principal factors has been discussed in the following sections.

#### 2.2.1.1 Based on objective

In general, research objectives describe what is expected to achieve. Research objectives are used on the basis of which research works have been divided. It has been discussed as below:

##### 2.2.1.1.1 Map understanding methods

The work of map understanding started with a cartographic pattern recognition system which has based on homogeneous parallel algorithms [92, 223, 290], automatic map recognition system and map recognition driven by a query that has based on template matching [152] and multi-angled parallelism [332]. Few works have been done in legend driven map interpretation which has adopted weighted bounded classifier, but they are noise sensitive and relies on separate map layers as an input [271-273].

Studies have revealed that recognition of symbols or objects from map have been primarily based on most distinguishing characteristics of it and their differences in color or shape. A symbol has been an essential component of a topographic map. Also, letters and numbers on topographic maps provide additional information about the terrain. Their recognition based on statistical and structural features has been important in the development of map understanding system.

Current research approaches to map understanding can generally be classified as bottom-up or top-down, semiautomatic or automatic, paper-based map or digital map understanding. But none of the methods addresses the complete solution for map understanding. They mostly considered interactive or user intervention or more concerned with vectorization rather than understanding or interpretation. The researchers who worked on map understanding have considered limited map objects and they have performed accuracy assessment as well as validation on the small map area. In the bottom-up approach, small groups of connected or physically close pixels have been analyzed. Thus, interpretation emerges from the information of an image towards abstract entity descriptions. Some of the works reported are having an interpretation system for graphic images, through vectorization and primitive extraction [4]. A promising approach [295] has been proposed, which has developed a learning utility under the human operator control for map analysis. The Japanese MARIS system has adopted a bottom-up strategy which forms, vector database based on object recognition. However, human intervention has been required to edit and correct the wrongly recognized objects in order to modify the system performance. The work has supported the digitization of some specific map layers, but their interpretation remains the problem to be solved. However, top-down methods utilize knowledge or pattern formed earlier. Systems typically start with an abstract description of the entities and continue by searching for them on the map. Mostly, the Top-down strategy has been used in digitization of topographic maps. To digitize German topographic color maps, PROMAP system has been developed by B. Lauterbach et al. [173]. Symbols and objects have been identified at the raster level and further vectorization has been performed in PROMAP. The system has been knowledge directed and requires abundant prior knowledge.

The work [85] reported highlights the idea that interpretation of graphics should be done at both syntactic and semantic level. Syntactic recognition involves classification of symbols in a document based on their shape, whereas semantic recognition includes methods for assigning description or meaning to the recognized symbol. Cordella and Vento [75] finds that system solely based on syntactic level, but cannot achieve the good and reliable result without the semantics held by symbols. An agent-based system for recognizing symbols in sketched documents is described by Casella et al. [52]. The process exploits the knowledge about the domain context to recognize symbols at a lower level. A statistical approach has been used in which typically nine features have been extracted to compare with the symbol prototypes using statistical analysis. The approach also partitioned the sketched elements like symbols, connectors, etc., which needs the minimum five training examples per symbol class.

Cadastral maps with the Redraw system have been developed by Mayer et al. [202]. In the work, relating knowledge about the map entity that is to be analyzed has been provided in the recognition module using simple heuristics. Simple algorithms have been developed to recognize the hatched area, parcel and closed boundary. This procedure exhibits limited scope. The system [3] developed, has provided a map symbol recognition approach which has based on Hausdorff distance and Neural networks. This exhibit recognition of map symbols using the traditional approach of overlaying. In this system, users may adjust symbol properties, initiate training or allow retraining in order to minimize false alerts or incorrect match. It has failed in matching a filled symbol. It generates lots of false positives match due to threshold driven approach. It lacks a way to address the human based approach for automated map understanding problem.

#### 2.2.1.1.2 Map layer extraction methods

Kasturi and Alemany [152] has developed an Information Extraction method for Paper-Based Maps. They have developed a Query Processor and image processor routines to perform symbol recognition. But the approach has failed to handle symbols of irregular shape. The system has not provided good recognition result for occluded, discontinued and intersected map symbols. The symbol recognition capability does not provide a solution for the multicolor map.

Khotanzad and Zink [164] have worked on the paper-based topographic map. They have developed Color key set technique to segment map in layers. They used combinations of RGB color histogram analysis, Valley seeking algorithm and A* search algorithm to extract layers of information. They have succeeded to overcome the difficulty of aliasing and false colors. The developed method has been able to locate valleys on the topographic map, but the still scope has been limited. It deals with feature extraction of contour only but lacks human understanding about semantics associated with contour and other objects also.

Another remarkable work [62] that has been carried out for recognition and extraction of contour lines have been reported. This system has separated and reconstructed color layers based on color key set technique and Eigen line fitting algorithm respectively. This approach has achieved contour line filtering and segmentation method. But this approach still has not been efficient for the separation of other linear objects. The scope has been limited to contour line extraction only. It deals with issues of thicker lines and larger gaps in the contours and the reconstruction of contour lines but does not provide a solution for its interpretation.

Thus, most of the map understanding scheme follows the traditional approach of overlaying for matching but unable to interpret filled symbols. Also, threshold driven approach generates lots of false positive match. It does not provide a way to address the human psycho-visual approach for automated map understanding problem. Frame-based image interpretation or application of semantic net have not been proved to be efficient for extraction of map objects due to geometrical fuzziness. Previous work has more focus on image processing for information extraction or retrieval of objects. The research work on map symbol description methods and learning strategies to make the machine understand topographic map have not gained much attention.

**2.2.1.1.3 Segmentation methods**

Actual map understanding has been highly subjected to making the choice of segmentation approach. The performance of the recognition process relies on segmentation scheme. The initial step in the map understanding has been the separation of map objects. The color distinguishes the main classes of map objects. However, the importance of color in topographic map creates several problems in effective layer separation such as color aliasing, uneven colors, false colors [164]. A lot of work has been done in developing the most efficient color segmentation scheme using thresholding, histogram based methods, region growing methods, clustering methods. Spectral components, i.e. color space (e.g. RGB, HIS, etc.) plays an important role in color segmentation. The work [88] reported, have used hue channel to calculate the mean and variance for recognizing the types of soil to develop soil survey inventory. The transformation of RGB color space into another color space has been performed in this approach. Khotanzad et al. [164] have developed a method to generate a color key in order to discriminate linear and area objects of USGS topographic maps and clustering method using histogram analysis of topographic map has been applied to extract contour lines. The work [152] proposed, has performed layer extraction from USGS maps using the gray version and color-coded map and further extended for color coding [164]. To separate contour lines from common conditioned topographic maps, Rids et al. [263] have developed parameterized edge detector, considering color and the vector angle. They have also developed a saturation-based method to combine hue and intensity. Also, the number of colors has been reduced using RGB cubes for extraction of contours from maps. As discussed earlier, Khotanzad et al. [163] have developed a color key set technique to overcome the problem of false colors, color aliasing. However, all researchers mentioned above have selected the color feature of map entity, which has the ability to segment topographic map of any type or any scale. But for map segmentation, selection of color space has been one of the major issues in map segmentation [28, 63]. Hence the hybrid color space consists of the robust features describing a topographic map [250], have used. The database consisting of segmentation of natural images carried out by human have been presented by Martin et al. [198]. They developed an error measure which shows consistencies between human segmentation and other segmentation granularities. Further, they have evaluated the performance of segmentation approaches and measured probability distribution based on Gestalt principles and image region statistics. Arbelaez et al. [23] have employed a hierarchical image segmentation method based on spectral clustering and posterior probability detector.

Most of the recent segmentation methods generally result in the identification of false positives which helped in achieving a higher overall recognition accuracy. However, most of the above methods do not consider inter-pixel statistical measure or correlation and global appearance. Hence, such methods usually fail to extract map element when the foreground and background have identical color.

#### 2.2.1.1.4 Pattern recognition methods

Interpretation of topographic map requires the efficient method to recognize pattern either in map symbol geometry/shape or in feature space measurement. The pattern can be a graphical feature or visual structure. There has been a prevailing research present in the field of shape pattern recognition area. Prerequisite of this pattern recognition is the suitable object description method. Pattern recognition performs two basic functions first, a description of the pattern and another, classification of the pattern. A typical pattern recognition system generates a description of pattern and performs classification based on that description (i.e., the recognition). Shape analysis plays an important role in pattern recognition.

The methods most commonly used in the representation, description, and classification phases have been reviewed. A basic assumption has been that the object descriptions have to be composed of observable attributes of the objects. The design of pattern recognition involves 3 aspects the data acquisition and pre-processing; feature extraction and representation; and decision making.

A statistical approach has adopted decision-theoretic concepts to discriminate objects based on their set of quantitative characteristics [59, 95]. The statistical approach uses the probability distributions to determine the decision boundaries in-between each group/class by the explicit specification or learning [82, 87]. The global features, like moments [53, 131, 300], mathematical morphology [137] and Fourier descriptors [340], have been used in shape description. There have been several statistical methods that can be applied in feature extraction phase. The classification task in the statistical approach uses feature vectors obtained from feature extraction phase. The classifiers such as template matching, Bayes' rule, ANN, k-mean have been performed based on the similarity measure, probability distribution, decision boundaries and clustering centers respectively [87, 136, 102]. Theorized process of human recognition involves recognition of a pattern or shape of an object based on characteristics of objects and human classification decisions made on the basis of the similarity between the extracted features and a feature description developed for each group [224, 253, 309]. The globally based descriptors [33, 165, 312, 343] show fault endurance to object deformity since they incline to remove little change or variation in the descriptor. Few researchers [31, 267, 302, 303] have combined structure and global descriptors as well as integrated different classifiers to enhance their efficiency. The system [267] has been implemented for graphical symbol recognition with the combination of many features such as solidity, eccentricity, angular features.

Structural approaches use syntactic rules or grammar to distinguish objects from another group of objects. This approach [101, 155] consists of grammars to represent shapes and arrangement between shape components. The recognition process can be controlled by top down or bottom up parsing. Several parsing methods such as a string or stochastic grammar, tree, graph have been proposed for shape recognition [240]. It may use a general measure of similarity between two structural representations. For the problem of map interpretation, the syntactic approach has not been as efficient as it is highly sensitive to noise. However, the topographic map has been highly crowded and often exhibits incompleteness due to overlapping or intersection of objects.

Thus, structural pattern recognition systems generate feature vectors that contain morphological aspects of objects to consider the visual representation. The morphological ordering in between primitives attributes and feature vectors of primitives have been supported by describing primitives' relationship. The grammar based interpretation of engineering drawings or diagram has been developed [46, 146]. The use of attribute grammar has been proposed in description extraction phase in diagram interpretation [46]. The engineering drawings have been interpreted, that has based on the integration of prototypical elements in the drawing [146]. The method constructs it through low-level image processing/analysis routines and recognizes it using the parser. From the literature, it has been observed that syntactic approach is having very little scope in topographic map object recognition. The object description using this approach does not carry complete information, so it would be not the best choice to use it in this problem domain.

The hybrid approach has integrated the characteristics of both statistical and structural pattern recognition. The methods reported above have not been independent and attempts have been made to develop hybrid methods [101]. Attributed string matching and hierarchical rule matching have been a hybrid approach that has reported in [298]. The work [251] reported a mechanism for combining global and structural feature [342] matching in a single framework. The researchers [251] have argued that efficient and correct object recognition approaches should employ hybrid approaches.

To use learning techniques along with robust pattern recognition approach or hybrid approach would be promising to discover the precise relevance with visual understanding is one of the new approaches. Also, expressing relationships in terms of discriminate or membership function [98, 208] gives very effective pattern recognition. It would introduce learning as a broad image understanding tool in map understanding domain.

#### 2.2.1.1.5 Neural network

The process of aggregating raw image elements to identify and follow discontinuous chains of symbols in digital topographic maps has been proposed by the investigators [104]. The algorithm uses an artificial intelligence kernel that handles three different adjunct processes: to pre-process the pixels in the region, to extract the recognized symbols, and to assign a key to each symbol. Gestalt rules have been incorporated to make a most effective grouping. They have also described the problem of the acquisition of discontinuous lines such as dashed and dotted lines from topographic maps. The work [323] has suggested neural network (MLP) to separate and extract text layer and linear objects from the map. They have used the color intensity and gradient values as an input to MLP but they have been failed to perform well for too dense geometries present in the map. They have not addressed the problem of color aliasing and false colors imminent with topographic maps.

Artificial Neural network has been used in modeling nonlinear problems and found that they have been performing well as compared to other statistical methods [278]. Girshick R. et al. [109] have integrated convolutional neural networks (CNNs) to bottom-up region proposals and supervised pre-training in order to locate and segment objects from an image.

#### 2.2.1.2 Based on type of Map objects

The literature has proposed to simplify the map object extraction task through an automatic image interpretation. The literature has been subdivided into more specialized problems like the extraction of buildings or roads and natural objects like vegetation or water. Surveys are mainly focused on topographic map feature extraction have been discussed below.

##### 2.2.1.2.1 Area recognition

The boundaries of map objects provide useful information about the water reservoirs land use or land cover area for evaluation and monitoring in different applications. Hydrographical layer (e.g. river bed, lakes, tanks) is a useful information source for detection of water resources, flood prediction, urban development, etc. Over the year this information extraction has been done by manual digitizing or photogrammetric method to determine the extent of landforms. This procedure has been expensive, error prone and requires lots of efforts [84]. However, these methods also lead to misclassification due to interference, present in different map layers.

In the work [292], an interactive system for recognition of abstract regions in cartographic maps has been developed. The researchers have built a region candidate generator and region synthesizer for region recognition. They have used a hierarchical structure and attributed grammars. Thus, the parser for checking the conformity of cartographic signs with the specified map syntax has been implemented. The generalization of map object, i.e. new map symbol has been assigned to the newly recognized region. The recognized region candidates have been evaluated with reference to the definition specified by the user. However, approach ignores the use of grouping criteria that are more specific and important to various types of building.

##### 2.2.1.2.2 Symbol recognition

Research in the field of symbol recognition has suggested that efficient symbol representation and symbol discrimination methods would be obtained by merging by a hybrid approach containing both statistical and structural approaches [47, 79, 236]. Most of the literature reviewed consisted of many approaches to locate and recognize symbols have been already discussed in the previous section. Syntactic pattern recognition or structural pattern recognition is a form of pattern recognition, in which each symbol can be represented by a symbol, nominal features, and attribute values. This represents a pattern, in the presence of more complex interrelationships between attributes. However, statistical classification uses flat, numerical feature vectors of fixed dimensionality. To efficiently recognize structural patterns of symbols on a topographic map requires spatial and structural properties. The approaches [185, 217, 237] developed, used the knowledge and demonstrated the use of a set of rules to find symbols in the images.

Varieties of symbol recognition systems have been studied by researchers [41, 64]. The system [261, 271, 272] has been designed to interpret topographic maps. The input to the system has been individual map layers. Weighted nearest neighbor classifier has been developed to identify symbols on the map. The system [88, 173] have applied color based segmentation and vectorization on a topographic map. They have employed ANN to extract symbol structure primitives. The knowledge driven interpretation has been applied to derive the relation between map symbols and prototype concepts provided by the user. The hypothesis and verify paradigm have been used to interpret USGC topographic map [217]. Specifications of map symbols have been extracted from the map using offline training. The line, area objects are recognized by generating and verifying the hypothesis about map entity. In the graphical logos recognition system developed by Rusinol and Llados [264], a set of local features and the use of a bag-of-words method have been used. Spatial coherence rules have been added to reinforce correct hypothesis about the logo.

Some researchers [80, 225] have developed a method to find the symbol in the neighborhood of already recognized symbols based on the knowledge base and contextual reasoning. The interpretation of a small part of the map has been carried out using a small set of rules and limited specification of symbols. However, a significant amount of computation resources and knowledge base parameter specification have limited the scope of the system.

#### 2.2.1.2.3 Text recognition

The text has been an important map object which represents toponym i.e. administrative names, additional information about other map objects distance stone number or canal line number. The map text has been used to provide an abbreviation for some character string, e.g. post office has been represented by 'PO'. The recent studies concerning map understanding procedure have emphasized the character/graphic separation. However, very few encouraging work on recognition and understanding the labels has been reported so far in the literature. The work [260] has reported for developing an algorithm to improve text/graphic separation. The researchers have adopted the color separation approach using clustering method. Similarly, Kasturi and Alemany [152, 154] have developed an algorithm that has emulated human understanding about characters to locate, extract spatial objects in maps.

The work [51] demonstrated a way to separate overlapping text and graphics method based on the difference between the stroke segments present in characters and those in graphics. The researchers [313] have developed an algorithm for separating overlapped characters. They have used OCR to define orientation, the size of characters and extrapolation of curves and lines have been carried out to separate graphics from the characters. They have succeeded in characters grouping based on consistency constraint effectively, but have performed character separation or extraction and have not addressed character recognition/interpretation. Different approaches [99, 100] have proposed to extract textual information layer from topographic map. The approach employs knowledge base driven template matching method.

The text extraction method [69, 117] based on a training-by-example paradigm, has developed. The human efforts have been required to separate text pixels. The orientation of text has been determined by the skew detection method. The commercial OCR algorithm has been employed to recognize text from raster maps. The researchers [217] have generated the hypotheses about the potential characters in each text label and the locations of these text labels using a gazetteer. The auxiliary information (e.g., gazetteers) used in these techniques has been usually not easily accessible for map images. Text recognition and interpretation have been a very important task in which a lot of research work has to be done. In topographic map understanding, the main difficulty lies in that text overlaps other map objects. The potential characteristic of a text detection algorithm is that it has to be the font, size, and orientation independent. The approach [243] has applied connected component processing to determine the geometry of connected components. They have rendered recognized string to connect centroids of each character in the string. However, a method has been proved ineffective when the height and width of characters are different. Rusinol M. et al. [265] have developed a patch-based framework using bag-of-visual-words model based on SIFT descriptors. They have employed semantic indexing technique to refine the feature vectors. The developed algorithm yields good results for handwritten and typewritten text in the historical document. Roy et al. [262] have proposed a generalized model based to increase the quality of images and to detect text from images. The proposed approach takes into account, an edge and it's neighbor information to obtain a mathematical framework for enhancing low contrast information in scene images. Roy et al. [259] have developed an approach to recognize a multi-oriented text from the graphical document. For recognition of multi-oriented text, sliding window's path has been estimated. The features extracted from it have been given to the HMM system for recognition. Roy et al. [258] have performed a remarkable work for text line segmentation from the historical document using foreground and background information.

Most of the systems have considered the extraction of some specific types of objects and from maps. The text extraction task has been hard as it often touches with other map objects. Also commercial OCR has employed in almost all systems which works well for horizontally aligned text and failed to handle the non-horizontal without human efforts. The domain of topographic map understanding has a significant amount of scope in automatic text understanding.

#### 2.2.1.2.4 Contour recognition

Contour line has been most distinguished and important object of topographic maps. It connects points of equal elevation of the land/terrain surface. Topographic map has been important source of information on terrain data. Most of the geographical information system has been performing applications like digital elevation model, 3D terrain model, etc. for which terrain data have been prerequisite. Contour line has been the most significant element of topographic map as greatly used in Digital Elevation Model (DEM) data. Hence, contour line recognition and extraction have been most vital tasks in topographic map processing. The researchers on topographic map processing have emphasized recognition and extraction of the contour line. Some of significant methods have been provided below:

The developed approach [274] has used fuzzy set for filtering contour lines. The contour extraction has been accomplished in two steps. Firstly, the filtering approach has been employed to identify image structure and noise and secondly, application of fuzzy rules to develop the estimates. Further, the work has extended by applying color image segmentation to segment contour layer [275]. The morphological and filtering have been employed to remove non-contour elements. They have also worked to identify cross points and terminal points to reconstruct a broken contour line.

The Haugh transformation approach has been applied which has not reliable for unambiguous contour lines on the map [332]. It will require optimal segmentation and well defined line segments as proposed in [274]. Many investigators [105, 164, 274, 275] have reported the works using RGB color space in color segmentation. The color information has been one of the important constraints to recognize and understand the objects on topographic maps. The contour lines have been suffering due to non-uniformity of colors due to variations in contrast with the background. The color key set technique has been built for the color segmentation problem. The line fitting algorithm consisting of eigenvector has been used in color key for foreground and background pair composite implementation. The pixel plot in RGB space shows the ellipsoidal pattern in which one end denotes a linear object, i.e. contour and other end shows the background.

Some researchers have developed an algorithm that can be used for tracing contour lines automatically from contour maps separated from the topographical maps. They have proposed an advanced Moore's Neighbor contour tracing algorithm. The proposed approach has been tested on a number of topographic maps and gives satisfactory results and proved time economical to recognize the contour lines compared with other existing algorithms [244]. Many researchers have worked a lot to yield a technique to automate terrain information extraction from topographic maps. An approach to extract contour lines from topographic maps has been devised [174]. They have developed a procedure that supports automatic vectorization of clean contour and drainage. Some researchers have developed an image based approach based on mathematical morphology operator for reconstructing contour lines [287]. Most of these procedures failed at discontinuities.

Hierarchical template matching algorithm has been used for extracting text, but it fails to extract contour lines [99]. The researchers [99] have developed geometric properties which have been based on global topology to recognize contour. This method uses Delaunay triangulation to thin and vectorized contour line.

Deformable model and field flow orientation method have been developed to extract contour lines [350]. For extraction of contour lines, the researchers [330] have described the gradient vector to calculate diffusion at an edge pixel in the gray level image and to extract contour lines. Many contour tracing algorithms have been used in several works, but each algorithm has its own usefulness and limitation factors. Mostly many algorithms fail to trace and identify gaps or holes present in the pattern. Hence, Gap searching algorithms have to be employed prior to tracing of the whole contour line. All these solutions can give an exact solution for contours where all lines are spaced properly and isolated, but the applicability of these approaches is limited to a contour where they are intersecting to other symbols and very closed to each other. The techniques based on line-tracing algorithm provides recognition of line pattern and helpful to overcome the difficulty of gaps and thick lines, but has been unable to handle the same colored elevation values and highways.

#### 2.2.1.3 Based on interpretation technique applied

The existing information extraction techniques either using satellite image or geographic map has been devised which comprises digital image processing operations on the basis of object representation depicted on them.

There have been two strategies named as top-down and bottom-up strategies for interpreting symbols. Bottom-up strategies start from the lower-level individual base element's data (the bitmap) and tune in many levels until the boundary between the sample and the set of the prototypes has been diminished. Ascending to higher levels of abstraction, bottom-up methods use a general description of the object to be found. Human cognition has been based on a bottom-up paradigm which works on incoming eye data and turned into meaningful image or representation of the brain that has interpreted as a perception. are used in most of the recognition systems. Hence, bottom-up approach has been used in most of the information processing techniques.

##### 2.2.1.3.1 Low and mid level methods (Bottom-up)

A bottom-up approach comprises a series of processes to identify objects and to recognize it [80]. The basic problem in object search and recognition in topographic map is due to overlapping and intersecting of map objects. The topographic map consists of various types of map objects like line, points, polygon/cell type and various conventional signs for the reading map. Most of the topographic map interpretation approaches have emphasized the detection and elimination of the line object. The bottom-up processing has been applied by any researchers for linear object detection in which they have usually employed morphological operation, including thinning algorithm followed by an approximation of the polylines [75]. Thus, the bottom-up process may constitute morphological operations, segmentation and classification steps in the perceiving object as a meaningful entity.

###### 2.2.1.3.1.1 Morphology and filtering

Mathematical morphology has a set theory based approach that has been employed in image processing operations. Based on a mathematical framework, geometrical shape and their quantitative and topological measurements of an image element can be obtained using operations such as dilation, erosion, union, intersection, complementation, thinning and other derived operations [176, 199, 281].

Morphological opening operations have been applied to remove noise from the satellite image and identify road object [341]. The investigators [57, 156] have applied mathematical morphology to detect linear objects in an image. The work [275] has adopted morphological operations and filtering methods to remove unwanted segments from the digital topographic map. In many reported works [17, 50, 65, 77], the gray scale morphological algorithm implementing edge detection and intensive filtrate usage has been employed. The mathematical morphological operations have shown a great contribution towards image or map interpretation [7, 8, 9, 10].

#### 2.2.1.3.1.2 Segmentation and Classification

The segmentation of topographic map can be considered as a pre-processing step or prerequisite. In automated map understanding process, after segmentation the desired object primitives or object descriptor has to be identified. However, classification of derived feature descriptors has been the proceeding step. Feature vector consisting of quantitative or numerical measures undergoes classification task and classify them into a particular class. Generally, all image understanding or analysis system performs segmentation and classification tasks. Some research work is done in the topographic and geographic map has been highlighted in this subsection.

The researchers [62, 164] has used a color key technique to provide a solution to color artifacts problem which has been introduced in topographic maps and to separate map symbols in different color layers. This method has failed for poorly conditioned maps. The topographic map has been segmented through unsupervised fuzzy clustering method based color image segmentation [348, 349]. The 2D histogram thresholding has been used in which image has been considered as a combination of two classes, first, object class and second, background class. Fuzzy entropy has been based on 2D thresholding. This approach has not handled the situation of the mixed colors due to the use of limited consideration of spatial relationship. The investigators [179, 181] have reported seeded region growing algorithm for segmenting topographic maps, making use of the local image plane, color space and connected regions on the map. However, this method suffers due to the selection of initial seed and parameters setting. The histogram threshold has been widely used in gray or color image segmentation [54, 61, 227, 228]. It has been most efficient and simple technique, but it has not proved to be effective on low-quality images.

The method [254] has been working on the map tiles where, on each tile, the transformation of Voronoi distance has been computed. The templates formed for symbols have been overlaid on the map, and the Hausdorff distance measure has been employed to locate symbols. The value of the distance threshold determines the number of candidates symbols. The map region has been provided as an input to a neural net, for the final decision. Neural net has been designed for each map symbol separately. In the reported work [271], the centroid of each component has been determined. The classification has been performed based on a weighted nearest neighbor algorithm. The training set has been implemented and increased in user feedback/verification mode. Myers et al. [217] have developed a feature extraction system based on hypotheses and verify the model. Incomplete symbol and noise have been handled easily in this model. Geometrical features have been used to describe symbols and ranked. Furthermore, higher ranked objects have been recognized used to identify symbol to validate hypotheses about the presence symbol.

#### 2.2.1.3.2 Mid and high-level methods (Top-Down)

Top-down approaches for pattern interpretation have been suggested that has especially suitable for interpreting objects or character strings from topographic maps or other documents [80, 217, 254, 315]. Top-down approaches have been more applicable in, a verification based approach which has used higher level contextual knowledge to verify interpretation notion [217]. The top-down approaches have been applied to various applications to recognize symbols from several types of document images [80, 315]. The top-down strategies use the model or efficient template which has been used to evaluate the hypothesis of the object to be found or estimated likelihood. In successive iterations, the model has been refined.

##### 2.2.1.3.2.1 Knowledge Representation and Modeling

The success of top-down approaches has been characterized by the amount of context and knowledge that has been available during pattern recognition [108]. Some of the research work has been provided here, which have also demonstrated the use of knowledge base and contextual information for information extraction and recognition of map symbols from topographic maps. A detailed study [200, 201] on automatic recognition of object has been provided. These works also define criteria for a model of knowledge representation and mapping between model and image. It allows the computer to operate like a human being and use rules and model to reason. The most effective and flexible knowledge representation and manipulation have been required for it. The complete automatic implementation by such an algorithm has been difficult. Various works done in knowledge representation in satellite image interpretation and their comparative study have been reported [288].

Ebi et. al [88, 173] have developed knowledge based image analysis system. The objective of the system is a hierarchical structuring of the map with map objects and relations between these objects from top to bottom. The knowledge has been formulated into concepts and instances. Further frames have been used to represent a concept and instance relationships. The instantiation of concepts gives actual decisive situated in interpretation module. The mechanism for instantiation of a recursive structure has been driven by on a monotonic deduction rule. The efficiency of the method has been proven on a real map scene. The efficiency of currently realized semantic net lacks the effectiveness for the acquisition of complex map entities.

The use of classes and frames for knowledge representation has been demonstrated by the investigators [21, 118, 206]. The intelligent algorithm has been devised to manipulate knowledge, employing forwards and backward reasoning. This approach progressively enhances knowledge in the system.

Template based system, has been often applied, in spite of the limitations occurred due to the representation, rotation and scale dependence, so that its applicability has been limited to a very specific domain in the context of symbol recognition. In template matching, the test image has been matched against the candidate image using similarity measure. However, variation in orientation, the interconnectedness of topographic map entities often generates distortion in templates. Template matching based on auto and cross correlation has been employed [221, 222] to obtain an acceptable recognition rate for a small part of the topographic map of size 128 by 128. The morphological arrangement of structure primitives has been devised to generate a map object's candidate representation [219, 220]. The BPANN has been used for classification. Unfortunately, training of the ANN with distorted candidate images and managing with a computation of vague similarity is a very time-consuming and computationally intensive complex process. For edge or line detection, Basak and Chanda et al. [32] have presented two connectionist models for mid- level vision problems, namely, edge and line linking.

Very limited graph-based approaches have been found in the map interpretation problem domain. The work [184] has been demonstrated for extraction of building based on breaking points of structure. The house structure has been identified based on contour and converted into map graph containing nodes and chains. However, this method has been demonstrated for building and roads only. A neighborhood graph concept has been implemented to extract quarters buildings from the French cadastral map [249]. The approach has been based on learning of prototype of the building using a genetic algorithm and dissimilarity measure. The results have been refined by pruning of the graphs. However, graph-based techniques have been facing the problem of high computational cost. Also, all the approaches mentioned above require the rigid definition of a prototype. Generally, such a definition can be provided by an expert in problem domains. The approach has been suitable for the problem requiring a few prototype graphs of small size but becomes unstable when the number of prototypes increases.

#### 2.2.1.4 Based on sequential steps utilized

Map Understanding process exhibits a simple strategy containing sequential operations which start from the processing of raw image data to abstract object entity recognition. The process starts with retrieval of map entities through segmentation techniques and feature extraction from them. Secondly, incorporating classification process on the extracted features. The whole process can be instantiated into several phases. In the first phase, i.e. the representation phase, for preparing the map image for computer processing. The second phase of identifying and describing the symbols located, while the third phase for classifying and recognizing them. The above strategy would be further refined as follows:

1. Pre-processing
2. Map Segmentation, feature extraction, Representation, and Description
3. Classification
4. Interpretation and Understanding

Figure 2.1 gives an overview of the basic steps and the dependencies between them with the help of flow graph.

##### 2.2.1.4.1 Preprocessing

The main objective of the preprocessing phase is to reduce noise and to represent map to make the prominent differences in the image notable. Most of the research focused on the extraction of each set of objects from a map in separate layers. The path-finding algorithm has been implemented to find gaps and discontinuities in symbol boundaries [164]. The algorithm has not been modified for dashed and continuous lines such as contour lines, and thus lack robustness to process other map symbols. Soille et al. [287] have employed a morphological filter to remove small objects or segments in order to produce a clean binary mask of the contour lines. The thresholding and edge-based segmentation algorithms have been reported [266, 347]. Some researchers have worked on image processing and segmentation domain in order to avoid distortion or to correct distortions. But no such a general or optimal approach has been found to process topographic map.

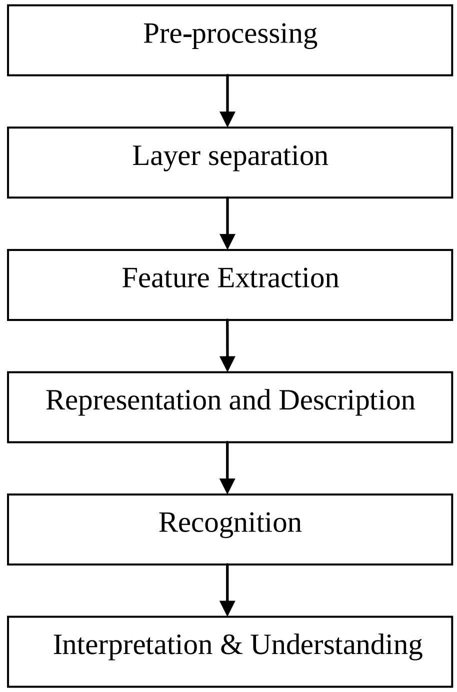



***Figure 2.1 Flow graph of general map understanding system***

### 2.2.1.4.2 Map Layer Separation

Map layer Separation has been a prerequisite for retrieval of the object or any kind of information from topographic map [188]. Map Layer Separation or segmentation has been typically carried out to discover map objects and their exterior contour. Noise removal has been conducted in many map analysis system prior to the segmentation [205]. Further, map image has been partitioned into a group of pixels based on some common criteria and represent map in the form of some meaningful entities. The common characteristics which have been used to segment map into various kinds of entities edge, color, intensity, and texture. After binarization and some very preliminary processing, many researchers have used connected-component labeling [271, 272, 274, 275, 296]. Generally, it has been used to divide the map image into local and global feature comprising feature vectors. These feature vectors are further evaluated for classification. Connected component labeling of the foreground has been used to identify, distinguish symbol.

Many researchers have worked on the map the layer separation based on color space only. In the analysis of Indian survey maps, RGB extremes have been used in defining initial clusters [83]. Further, k means algorithm has been employed to map each pixel into one of a cluster based on minimum distance. This approach has been based on a high level of homogeneity, which has not always been true for a topographic map. Gray-level thresholding based on global value have been implemented but has been labor intensive and complex task requiring human intervention [80]. The investigators [164] have used Eigen line fitting algorithm in RGB color space to separate USGC topographic map layers. They have employed local window to classify pixels present between object and boundary. The same approach has been extended by Chen et al. [62] by developing a local window segmentation method with a line tracing algorithm. But the approach has been never tested on another map from the same vendor, so its' robustness have not been proved.

The histogram-based approach using LUV color space has been applied on German topographic maps in which, peak detection technique has been used to determine color cluster centers in the histogram [88, 173]. The researchers [179, 180, 181] have used seeded region growing algorithm. The most frequent and similar color values have been identified as a first layer and have been removed from frequency bins to obtain prototype of successive color layers from the image. The prototype has been provided as input to the region growing algorithm. This approach suffers due to excessive computation time and requirement of user specified parameters. Thus, obtaining optimistic segmentation approach has been a recurrent problem in a map understanding because of noise and interconnected nature of geographic features present on a topographic map.

#### 2.2.1.4.3 Feature Extraction

Several studies on feature extraction methods have been performed to quantify or numerically represent a map object. The researchers [96, 193] have developed a feature extraction algorithm for vectorization of topographic maps. In this work, they have developed an expert system for environmental planning tasks in which fifteen features have been extracted and defined for a generation of map descriptions. The feature vector has been obtained through several low-level image processing or morphological operations. It enables subsequent learning and adds the generalization capability to the algorithm. In fact, the various feature extraction schemes have been depending upon the map type/form (raster vs. vector) which have limited the applicability of the algorithm. This has been due to pre-processing and layer separation methods have been data dependent.

The Euler's number and Rutovitz connectivity number have been used to compute shape descriptor [83]. They applied initial noise removal and thinning to extract features from topographic maps. The work [37] reported using erosion and dilation operations. Region growing algorithm has been employed before incorporation of feature extraction algorithm. They have used freeman chain coding to represent a building contour to generate feature descriptor. In several research works, shape descriptors have been used. Hough transform has been utilized to form multiangled and multi-directional feature descriptors [34, 295]. Miyoshi T et al. [213] have used simple and complex geometric features such as width, length, connection, shape and their variants for building extraction from scanned topographic maps. The approach has been ineffective for symbol overlapping. In the work [180], the forest symbols have been extracted from a historical topographic map based on basic shape descriptions. These shapes have been then evaluated to the prototypical shape using similarity measures. The approach [306] reported, has been described to perform number interpretation in hydrography maps. They have applied size and rotation invariant Fourier descriptors and have utilized them in statistical quadratic classifier for recognition.

**2.2.1.4.4 Representation and Description**

The researchers [123] proposed a method utilizing structural details of map symbols. The structural rules have been formulated in the form of grammatical production in Logic programming language (i.e. in PROLOG). The system has considered the geometric primitives and interprets them by rule reduction methods. The researchers have implemented an algorithm to recognize trees, overlapped lines and other small geographical elements from bitmap images. The morphological operations and covariance measures have been applied to generate symbol description. Such a symbol descriptor has been robust to the map scale. Also, variations of these descriptors for the same symbol have been handled and recognized. The method [42] has been devised for cadastral map interpretation. They have adopted graph representation in which node represents regions and edges stand for the lines. The searching of the symbol has been performed by heuristics. The system [271] has been developed, worked on raster topographic map. They have used the (user-located) legend to initialize a table of models to be found in the rest of the image. Further, they have applied connected component analysis to identify connected segments or objects and for each connected component, global as well as local shape features such as area, shape type, hole ratio etc. have been computed. Shape description has been robust to scale, orientation, and translation.

In the topographic map, each type of symbol exhibits several numbers of instances and variation according to ground condition. So, several representative symbol instances have been required for a good training set that will produce more appropriate recognition rates. The size of training set can be increased with the help of the user. At first, the user will interactively correct the recognition when necessary. All the symbols identified and corrected by the user will help consolidate the classification. Once the system generalizes well, it can then run stand-alone without user interaction.

There have been several representation methods that have been used by many researchers to describe the pattern image such as list, string, and the graph [342]. Once a symbol has been separated from the background, it has to represent it using some representative shape features which have been robust enough to represent it uniquely [343]. For the development of the legend understanding prototype system, investigators [222] have used boundary encoding which emphasized on shape. One of the most common external space domain descriptors, boundary chain coding has been used to represent shapes [221, 222]. The graphical representations and string representations of symbols have usually recognized by structural matching methods.

For low-level image processing algorithms, representation phase has been concerned with finding corresponding points between images, or finding edges or lines in an image. Also, operations on with pixel intensities and colors have been considered as low-level operations, As discussed before, regions have then to be represented and described. Two main ways of representing a region first by external characteristics using its boundary which focus on shape and the second are to represent a region/symbol by internal characteristics using internal pixels which focus on color, texture etc. High-level algorithms have been mostly used in the machine learning research area. These algorithms have been aimed to perform the interpretation or classification of a map as a whole. It includes classification, symbol detection and recognition, interpretation. These algorithms have been devised for the training of a system which makes it understand the symbol if it has been provided with some unknown symbol by locating and detecting structural or semantic information of interest.

Recent reviews on shape analysis and the feature description details can be found [342, 343]. The symbols used in topographic maps have been made up of some specific shapes which have characterized by some morphological, topological and geometric features and used for description [186, 191, 342]. Various instances of a topographic map symbol have a variable appearance. This has been due to the overlap of map symbols resulting in noise or disrupts shapes. For a topographic map, it has been natural that map symbols touch or overlap other symbols. It necessitates selecting the features describing unique properties of a symbol to overcome the variability of its' different instances. In contrast, for recognition purposes, it has to be more convenient to use few qualitative features, especially if there are few different classes and the variability inside a class is great. A description must be stable, concise, unique, and accessible.

### 2.2.1.4.5 Recognition

In map understanding application domain the symbol has been affected by overlapping or intersecting with other symbols. Hence, in topographic map understanding incorporation of the recognition stage with simple graph matching procedures [271] or a query-driven template matching algorithm [152, 38, 291, 332] would not be effective as the comparison between the input sample and a set of prototype graphs would not yield a good result. However, the learning strategy constructing a set of samples representing the symbol class has depended on upon the all possible alterations in shape. Nowadays this problem has been under study. The extreme learning machine based classification approach has been reported by Pal [231] for land cover classification using multispectral data. The researcher has carried out a study for evaluation and comparison between the extreme learning machine and a back propagation neural network classifier. An automatic learning and recognition of graphical symbols in engineering drawings have been developed by Messmer and Bunke et al. [208].

To automatically extract the intersections of roads from raster maps, Chiang Y. Y. and Knoblock [66] have identified other valuable information such as the road format (i.e., single-line format or double-line format) and road width to help the extraction process. Chen et al. [58] have developed an approach to automatically recognize road intersection points based on a combination of different sources of information like ortho imagery and ESRI street map, from each of the sources to be aligned. In particular, they have provided an automatic solution for a conflating method by deriving a set of control points.

A method for recognition of abstract regions in a map has been reported [293]. The researchers have described a region in term of constituent objects. The region has been determined and its structure has been parsed using grammar-based approach. De Stefano et al. [291] have proposed the recognition phase in which the regions containing relevant symbol are identified by searching on the map with each symbol template. A bitmap image which has been more similar to the symbol in training set has been considered as a template. The morphological covariance function has been employed for recognition. They have tested their algorithm and obtained recognition rates ranging from about 78% to 89% on the average, for the five map symbols only.

### 2.2.1.4.6 Interpretation and Understanding

The research work which has been done in the interpretation of pattern have been most emphasized. Many approaches have been devised to extract information from special types of maps automatically. Most of the approaches have worked on separate map layers (e.g. hydrographical layer) and individual map (e.g., cadastral map or utility map) [5,138]. The most of the approaches have aimed to automate the data acquisition large scale (1:500 to 1:10,000) maps which possess low-density information. However, medium scale maps (1:10,000 to 1: 50,000) which show an abundance and variety of information have been not considered for automated data acquisition.

Some of the approaches proposed by different investigators have been provided in this section. Moreover, the automatic understanding of topographic map has been a still unsolved problem due to the complex, wide variable characteristics and massive overlapping of topographic map symbols.

In the statistical approach, the global shape features have been used in which discriminant functions have been employed [95, 123]. These features are very easy to derive and compute. But the statistical approach lacks robustness to recognize occluded objects. This has been due to the variation of the feature description of several instances of the same object, however, an efficient classifier which able to handle such a varied and vagueness may give a correct interpretation. Next, the syntactic/structural approach [46, 101, 146, 155, 240] have employed local structural features like arcs and segments as primitives to represent shapes. They have been flexible and sensitive to noise. Also, partial occlusion of symbols has been difficult to handle by the syntactic/structural approach [112] and may require dynamic programming. In addition, this approach requires more computation time. In template based approach, the test image has been matched against the candidate image based on a similarity measure. However, variation in orientation, the interconnectedness of topographic map entities often generates distortion in templates. Template matching based on correlation function have been implemented in the preliminary research work [220] and have obtained an acceptable recognition rate for a small part of the topographic map of size 128 by 128. Unfortunately, it has been found that distorted candidate images and their computation of similarity have been a very time-consuming and computationally intensive complex process.

***Table 2.1 General classification of methods and works on map understanding***

| **General Classification of methods and works on map understanding and interpretation** | |
|---|---|
| *According to the objective* | *According to the type of Map entities* |
| Map understanding general methods<br>Map layer extraction methods<br>Segmentation general methods<br>Pattern recognition general methods<br>Neural networks | Area recognition<br>Symbol Recognition<br>Text Recognition<br>Contour recognition |
| *According to the interpretation technique applied* | |
| Low and mid level methods (Bottom-up) | Mid and high-level methods (Top-Down) |
| Morphology and filtering<br>Segmentation and classification | Knowledge representation and modeling<br>Rules based systems<br>Template based systems<br>Graph-based systems |
| *According to the sequential steps utilized* | |
| Pre-processing<br>Layer separation<br>Feature Extraction<br>Representation and Description<br>Recognition<br>Interpretation and understanding | |

Here, it can be stated that the interpretation methods have not been necessarily independent and attempts have been made to develop hybrid methods. For example, attributed string matching has been developed as a hybrid of statistical and structural approaches. Thus, it would be promising to obtain a better segmentation and recognition scheme to develop learning and reasoning ability in the system.

Schematically in Table 2.1, classification of methods and works on map understanding which have categorized and described above have been summarized. Evidently, in order to review, the possibility that the same work has been included at the same time in various divisions of the classification that have been supposed.

## 2.3 A COMPARATIVE EVALUATION OF EXISTING MAP UNDERSTANDING/ INTERPRETATION SYSTEM

Eric et al. [254] have developed a system for automatic symbol and line recognition. The system has been made of several components like user interface, a symbol recognition engine, a knowledge base and a database. The recognition is based on Hausdorff distance and neural networks. The environment consists of four components: user interface, knowledge-base, image understanding and symbol database. They have used Hausdorff distance (h) to measure mismatch between a candidate symbol (M) and test symbol (I) at a specific point in the map by superimposing them on each other. However, the distance measure has not been useful to distinguish between good and bad matches. For small 'distance threshold', system misses poorly drawn symbols. Also, many false hits have occurred when the large threshold value has been selected. Hausdorff distance has not been sensitive to symbols touching or overlapping each other. The user must adjust the parameters to control false hit ratio. To achieve near perfect recognition Hausdorff distance has been combined with a neural network (back propagation neural network). Also, developed system has interfaced with legend editor for recognition of hand drawn map symbol and has not processed any scan or raster image of the map.

Malerba et al. [94, 193] have proposed automated system for Interpretation of vectorized Topographic Maps. The computational methods for the localization of map symbol in the cell and generation of logical descriptions of map cells have been applied to map interpretation task. Learning from Logical Descriptions of Map Cells has been incorporated to interpret vectorized topographic map. The approach has been suffering due to over and under-segmentation as a selection of grid size is critical in the localization process.

The problem of extracting distinct map symbols from raster maps has been addressed by Boesch [179, 180]. Shape descriptors and distance weighted triangulation have been used to identify map symbols. Symbol discriminator has been defined by a set of rules and the user has been able to solve discrimination problem interactively. However, the system has been effective for nonrigid symbols and detectability varies with a drawing quality and scanning resolution.

A hybrid approach for cartographic symbol recognition has been presented [38]. Shape features have been used to represent the cartographic object. The binary decision tree has been incorporated for shape classification task. The structural matching has been employed Shape classification  A decision-tree classifier (DTC) is used to identify the shapes of the individual components of a symbol for labeling of input patterns. Structural matching has been used to compare the prototype tree for the symbol under consideration. However, a strict match constraint has been imposed to identify the complete symbol. The system has not considered for interpreting the partial symbols present in the map.

The most of the template based interpretation approaches have considered the matched filter as well manual design. An entropy based method has been proposed to extract binary templates from the training set which includes all possible instances of a cartographic symbol to evaluate a template and assigned as representative pattern [291]. The unreliable pixels have been removed based on entropy threshold. The template found, assures good recognition rate for well-isolated symbol interpretation. However, distortions, high density of cartographic entities, superimposed to particular background configurations makes template matching difficult and ineffective.

Chen et al. [62] worked on the extraction of contour lines from topographic maps. A local window segmentation has been proposed to overcome the deal with gaps and thick lines. Contour lines have been separated based on color information. But in topographic map contour color have been mixed with the background color. To deal with this color aliasing or color mixing, they have developed color key set technique. The color key has been formed by the composition of foreground - background color code. Foreground color has been represented by extrema of RGB color space. The scope of the algorithm has been limited to the contour line filtering only. It has been tested on various scanned topographic map samples.

The researchers [88, 173, 297, 320] have developed knowledge-based topographic map analysis system. The efficiency of the method is suffering due to the high computational cost and variability of map entities as it has been not tackled. It is not proven a good solution for the acquisition of other map entities in the same map also.

An Interpretation system of Cadastral Maps has been developed [158]. The researchers used the developed system for recognition of building and parcel from the cadastral map. The cadastral map consists of building and parcel outlines with house numbers and parcel numbers. Main processing of map involves vectorization, segmentation, and interpretation of the building and parcel. The segmented objects have been represented using Data graph structure. The recognition has been performed by a back-propagation neural network model. The scope of this system has been limited to the cadastral map only.

An approach [164] has been proposed based on an $A^*$ search algorithm to identify gaps in the symbols from topographic maps. The algorithm has not been modified for non-dashed and continuous lines which may be parts of contour lines, and thus difficult to apply the algorithm to extract contour map from the source topographic map.

Takashi Hoshi has described an interpretation of symbols with hole features from a topographic map of scale 1:25,000 [130, 299]. They have selected two sets of shape features. First set comprising of a number of holes, the ratio of length to height, line width and diagonal connection. The second feature set includes the image size, inclusive relation, and separation. A thinning operation has been performed for feature extraction of geometrical feature points. Recognition of map symbols has been done by matching with original map symbols. However, overlaps of the line feature with another circular map symbol could not be handled. The scope of the system has been limited to, map symbols carrying a hole in their structure.

The major global approaches which follow context or concept understanding by either applying pattern matching, template matching, decision tree, learning techniques, top-down and bottom-up approaches have been reviewed. The summarization of comparative evaluation of existing map understanding/interpretation system has been provided in Table 2.2.

The topographic map understanding system may find an important application for the geospatial community; whether it may be used for land use planning and development are practically applied in map guided applications. Unfortunately, there has been no such a strategy for understanding and interpretation that can accommodate all its applications. The system that has been developed is used for recognition of  limited map objects on a topographic map. But, from literature review, it has been proved that the understanding of any map object, usually leads to the solution to what has been visually adequate and how it may be contorted. The ultimate objective of many map analysis/interpretation tasks has to discover the meaning of the map objects/symbols, e.g. categorizes the objects, provide symbolic/semantic interpretation of the map image. But no ready or complete solutions have been available for a topographic map. Most of the approaches have given emphasis on recognition of well-defined symbols and textual information from the map. But none of the systems considers information changes or missing information. Learning based system has gained null attention in map interpretation. One of the most obvious difficulty learning based system is the absence of a clearly defined training set which define what to recognize. Due to unavoidable tolerance to overlapping in a topographic map, there has been a strong need to define how to define the correct recognition techniques.

The most commonly used techniques have been briefly reviewed, and several representative papers have been summarized in this chapter. Also, literature on the image segmentation, feature extraction, feature description, recognition, classification, and interpretation has been reviewed. A scanned topographic map understanding using any numerical scheme requires a huge amount of computer storage and computational time for the recognition of map symbols and text without providing an accurate understanding of partial and intersected map objects.

***Table 2.2 Comparative evaluation of few existing map understanding/interpretation system***

| Sr. No. | Objective | Methodology | Achievement | Limitations | References |
|---|---|---|---|---|---|
| 1 | Map Symbol Recognition Classifier | Directed Hausdorff Distance And A Neural Network | The Hausdorff distance performs segmentation. It has no problem when symbols are touching or overlapping. It also rotates all symbols to the same orientation for easier use of the neural networks. | The human operator is needed to regulate the recognition process. The distance measure is sensitive to noise. | Eric Reiher, Fady Said, Ying Li, and Ching Suen (1996). |
| 2 | Automated Interpretation of vectorized Topographic Maps | Map Descriptor module for Generation of Logic Descriptions of Map Cells and machine learning tool in INGENS | Learning from Logical Descriptions of Map Cells is made possible to interpret vectorized topographic map | The segmentation of a map with a grid of suitably sized cells is a critical factor | Donato Malerba, Floriana Esposito, Antonietta Lanza, Francesca A. Lisi (2001) |
| 3 | Automatic Recognition of Topographic Map Symbols Based on Their Textures within the raster-vector conversion of maps | A texture based statistical pattern matching. | Assignment of the attribute of the symbol to the vectorized objects and removal of symbol polygons from vector data, the recognition rate is 95% (performance is evaluated based on correct, false positive, false negative. | A raw vector data model is needed for interpretation of map symbol | Rudolf Szendrei, Istvan Elek, and Istvan Fekete (2011) |
| 4 | Detection and extraction of complex map symbols from raster map | Shape descriptors and distance weighted triangulation method | Local Hough transformation to improve recognition rates; symbol discriminator is defined by a set of rules | Inefficient to detect line symbols; detectability varies from map to map; human intervention | Ruedi Boesch (2009) |
| 5 | Recognition Of Cartographic Symbols | A decision-tree classifier (DTC), Structural matching. | A hybrid (statistical/structural) approach is pre- sent, for scale- and orientation-invariant recognition of multi-component cartographic symbols. | A strict match is required in order to identify the complete symbol. Partial tree-matching is not considered. | Sushil Bhattacharjee and Gladys Monaga (1994) |
| 6 | Extraction of binary template from scanned map | The probability that the pixel (i, j), the reliability of its single pixels to obtain the final template; the entropy related to the single pixel is considered; template matching | The extraction of templates from binary images; the template is obtained by eliminating unreliable pixels determined by means of an entropy-based criterion | Distortions, high density of cartographic entities, superimposed to particular background configurations makes template matching difficult. | C. De Stefano, F. Tortorella, M. Vento (1995) |
| 7 | Automatic data acquisition from topographic maps using a knowledge-based image analysis system | Multilayer perceptron, contour tracing algorithm, Frame-based model, Truth maintenance system. | Separation of color layers, raster symbol and raster object recognition and vectorization have been achieved. | Problems in map interpretation may occur if the raster image is too complex. In such cases of conflicts, the instantiation of concepts of map objects may not be possible because of lack of appropriate structure primitives. A possible reason for complexity may be the overlapping of different map symbols. | N. Ebi (1994) |
| 8 | Extraction of contour lines and other geographic information from scanned color images of topographical maps | Color key set; The valley seeking algorithm; A* search algorithm | Extraction of the contour lines from a scanned Topographic map; lines, other objects such as black regions representing buildings | Usually extracted successfully, but while reconstructing it, broken contour line ends together with the proposed system. | A. Khotanzad and E. Zink (2003) |

| | | | | | |
|---|---|---|---|---|---|
| | | | and green area objects are also extracted; manually assigned elevation values associated with the contour lines can be used to render three-dimensional scenes of the terrain | | |
| 9 | An Interpretation of Cadastral Maps | Raster to vector conversion; Segmentation of symbols, dashed lines, continuous lines based on the independent algorithm; Recognition of symbols, using a neural network model. | Dynamic description of arbitrarily complex drawing objects; successfully classifies three disjoint layers: dashed lines, separated symbols, continuous lines | Interpretation results need to be accepted or rejected during a manual checking procedure; application specific. | E. Katona and Gy. Hudra (1999) |
| 10 | Contour line extraction from scanned Topographic maps. | Local window segmentation; Eigenvector line fitting; color key set, Thinning, and pruning algorithms. | The problem of the gaps and thick lines caused by the segmentation from the common conditioned topographic maps has been resolved. | Contour lines are getting recognized, but rest of symbols or objects get remains unrecognized. | Yang Chen, Wang, Qian, (2006) |
| 11 | Recognition of map symbols forms topographical maps | Hole and geometrical feature- aspect ratio | The method of extraction and recognition of a part of map symbol with hole feature has been achieved. | Overlaps of the line object with another circular map symbol could not be handled. Recognition is limited to, map symbols with a hole. | Takaki, T., and Hoshi, T (1990) |

On the other hand, exact contour recognition solutions have been available only for problems which involve landscape in which none or very few map objects has obscuring contours. Edge-based segmentation process marks differences in visual attributes. Edge detection has been fundamental to many machine vision algorithms but failed in segmenting an image into relevant regions. Toponym i.e. place name detection has failed and often missed place name string due to over or under-connected components. This kind of errors shows the limitations of a technique which has been based on connected components and the importance of the segmentation algorithm chosen. The procedure of template matching has not been acceptable for correct recognition of symbols as different instances of the same symbol may vary in orientation. Color image segmentation methods require the prior knowledge about the number of regions existing in an image. Adjacent clusters often overlap in color space, which causes incorrect pixel classification. Recognition systems have not been provided with sufficient provision for representing the uncertainties involved in its recognition and classification modules. Crude domain knowledge has not been extracted for an initial parameter setting of the Neuro-fuzzy system, hence, recognition result has been highly dependent on an initial parameter setting. Reasoning abilities of human to infer the decisions about the topographic map object class have not been implemented into any existing system. It may be concluded that a suitable segmentation approach based on criteria of color and the capability to decipher symbols and non-symbol, contour or non-contour objects has been very much essential for the recognition and understanding the map object. Moreover, modern AI techniques have been associated with pattern recognition problems. However, it has also been observed that the application of AI and fuzzy system associated with feature based image interpretation has been limited in the literature.

Most of the map interpretation system uses a digital raster graphic (DRG) resulting from scanning a paper SOI topographic map for use on a computer. DRGs created by SOI have been typically scanned at 200 dpi, but may include printing as well as scanning environment artifacts. It has been rarely used by mapping agencies and their distant users. On the other hand; raster map image consists of standardized color and usually used to avoid scanning environment and paper quality variance as well as their limitations. The DRG information extraction techniques perform well for images scanned by high resolution and quality scanners and but may not perform well when the image contains aliased and false colors. To overcome this difficulty as well as considering practical usages of the color raster map in TIFF format has been used in the present study. This map file has UTM projected and geo-referenced on the WGS84 datum to the surface of the earth. This format has been regularly used in GIS applications. The potential advantage of GeoTIFF map includes map projection, coordinate systems, ellipsoids, datums, and information required to establish the exact spatial reference. It's automatic interpretation will serve excellent solution for Raster map imagery analyses in various applications, Data revision, Map update and Map generalization and production process of topographic databases.

## 2.4 DISCUSSION

Based on the critical review of the existing literature, following points describing limitations of existing approaches have been noted:

1. Most of the research focused on the extraction of each set of objects from a map in a separate layer using various algorithms. No such a system has been developed to emulate human topographic map understanding.
2. Automated query processor and Image processor routines (skeletonization, line tracking, closed contour detection, symbol identification) have been developed for pattern recognition but only a query relevant portion has been processed and processing has been limited to binary image only. Also, it has failed to provide a solution to recognize filled symbols and to handle imperfections in map images such as overlapping of text and graphics etc.

3. Image segmentation based on region and edge integration has been developed in which the foreground object is clearly separated from the background, but resulting in the over-segmented regions in the background and have not considered color information.
4. A segmentation technique based on line-tracing algorithm provides recognition of line pattern and helpful to overcome the difficulty of gaps and thick lines, but it has been unable to handle the elevation values and highways of the same color.
5. For text extraction, especially when text has embedded in graphic components or when text touches graphics no assumption has been made about the character font, size, color or orientation. Some approaches have included Optical Character Recognition (OCR) package for text recognition. The OCR works properly for machine printed characters, however, it shows poor performance as text objects in the topographic map are highly orientated and obscured by other objects of the map.
6. Most of the map symbol interpretation scheme follows the traditional approach of overlaid for matching but unable to interpret filled symbols. Also, threshold driven approach generates lots of false positive matches. It has not addressed analytical approach of human map understanding of the automated map understanding problem.
7. The human operator or human intervention is needed to control the interpretation task.
8. Most of the approaches required raster to vector conversion process as well as raw vector data model for interpretation of the topographic map.
9. The formalized semantic net has not proven for the acquisition of map layers due to geometrical fuzziness. Also, feature based soft computation approach have not been used in the map interpretation.
10. Most of the approaches lack robustness as recognition rate varies from map to map, also, these approaches are insufficient to interpret partial map symbols.

Most of the literature available has been addressing the low-level vision approaches, however, high-level vision remains unsolved. There exists no such a system emulating human understanding ability to recognize patterns and to select relevant data or information in thematic layers for better analysis. In fact, challenges belonging to information processing as done in the human being have not been tackled for map understanding purpose. A critical review of literature has identified the following research gaps which need to be investigated:

1. The procedure of pattern matching has not been employed for correct recognition of symbols as different instances of the same symbol may vary in scale and orientation.

2. Color image segmentation methods require prior knowledge of the number of regions existing in an image and adjacent clusters often overlap in color space, which causes incorrect pixel classification.
3. Recognition systems have not been provided with sufficient provision for representing the uncertainties involved at every stage, i.e., in defining image regions, its features and relations among them, and in their matching.
4. Crude domain knowledge has not been extracted for an initial parameter setting of the Neuro-fuzzy system, hence the recognition result has been highly dependent on an initial parameter setting.
5. Human-based map understanding which has been characterized by legend reading have not been implemented into any existing system.

The possible solution tailored to research gaps has been identified. The legend and map reading capabilities of human to process the neural signals carrying description regarding map objects and resulted into understanding about topographic map object in the form of getting a semantic meaning of respective map object have not been implemented yet. It has been clear that map understanding problems have a strong resemblance to human mentation processes. The human recognize highly complex topographic maps very easily. They have the inherent capability to recognize patterns. They perceive colors and uses it in prototype or concept matching. Human uses object or symbol characteristics feature to recognize them, which may be termed as feature based matching. The human mentation processes can handle vagueness and exhibits, learning the ability. Thus, the possible solution towards the gaps in scope is to emulate the human way of reading maps, i.e. use of legend knowledge and human mentation process towards understanding. A fuzzy system which includes fuzzification, fuzzy inference system and output membership function may be of great help to enable the computer to model human map understanding. A fuzzy approach to shape analysis accommodating imprecise concepts, therefore, may be a significant consideration. In cases of complex patterns, the hierarchical or tree-like structure of simpler subpatterns has to be adopted. These structural characteristics primitives may be used for recognition of patterns. With the structural framework of knowledge and ambiguity in human reasoning, it may be possible to achieve intelligence by providing learning capability to a map understanding system. The neuro-fuzzy approach may be helpful to create such intelligence in understanding through the computer. So the initial problem is stated in terms of segmentation of a complex background, pattern recognition, which captures invariant properties of the object and interpretation of objects using inference techniques.

Most of the government agencies, surveying industries and distant users of the topographic map have looked for a pattern and automatic map analysis. In order to keep the computational involvements within a manageable range and to have a reasonably accurate method for the understanding of map with accurate classification and interpretation, the combination of Fuzzy system and Neural network appears to be one of the best options to imitate human map understanding. Actually, such a system can handle the complexity of the map and uncertain or incomplete symbols on the map. The development of automatic topographic map understanding system based on adaptive approach has been further necessary to overcome the problem of variation, complexity, and incompleteness of map objects. The system should also be capable of representing the visual representation of terrain and layer wise analysis of the map. The above observations and literature findings have inspired the author to undertake the present investigation. Fundamentally, what aim of the research is to combine a fuzzy and neural system with a feature-based approach be used to make the computer understand the topographic map efficiently and effectively and extract relevant information from it. Also, the area of computer understanding depends on generalization more than any other area. The main reason for research interest in map understanding stems from the facts that understanding has been the innate ability of the human mind and generalization has been one of the most challenging, and most useful skills a computer can have. In this research, the aim is to integrate human and generalization skill of the machine. Machines are more deliberate, more precise and less error prone to exhaustion and errors as well as far away from material reality and substances of the human mind which may degrade thinking and understanding also. Thus, computers have a place to implement an understanding of topographic maps and improve it by learning. In this research work, the challenges are two-fold. First, it has been needed to develop automated techniques that avoid the user input and utilize the input by itself to build end-to-end systems for extracting and recognizing map objects. Secondly, to develop systems that learn from the input itself, so that the more it can generalize on any Indian topographic map. Hence, based on all reviewed approaches, a way of integration of learning and interpretation must be implemented to achieve a flexible adaptation to changing situation in the topographic map for successful understanding the map and extract information from it. The general characteristics of the present investigation have been listed below:

1. The ultimate goal of map understanding has to be able to recognize map entities no matter what the circumstances (background, occlusion, etc.). As this has not a trivial to achieve, a step by step approach, starting from segmentation to symbol understanding has to be adopted.
2. The sub-goal is to investigate the analytical model of human man understanding and explore related techniques to extract geospatial information from the topographic map.
3. The performance of the system has to be validated based on different validation criteria like human/manual visual checking or interpretation. In testing, standard OSM topographic map data and manually delineated layer data have to be used to check the performance of the system.

Based on a review of literature, the salient scope of the research has been identified as:

1. Many difficulties in map image processing may arise because the data, tasks, and preprocessing results. Imperfection in map image processing may be due to grayness ambiguity, geometrical fuzziness, and a vague knowledge of object features.
2. Color has been the most dominant and distinguishing feature in the topographical map and hence it has been useful or even necessary for topographic map understanding through the computer. Color has been appealing for dealing with context information. Segmentation of the map image by considering this aspect has been challenging task
3. Map image segmentation will face problems in defining and setting thresholds for homogeneity in noisy or a complex map which has been characterized by multiple attributes.
4. The shape has been a prime feature for understanding the objects because human associate the definition of objects with shape rather than with color. The perception of shape provides a collective understanding of properties like size, form. It has no unique mathematical definition. Human analysis of shapes often makes use of imprecise concepts. So it has been inherent difficulty to enable the computer to recognize shapes.
5. Typically, a recognition system needs to classify an unknown input pattern into one of a set of pre-specified classes. The task has been easier if the number of classes is small and if all members of the same class are almost exactly the same. However, the problem becomes very difficult if the number of classes is very large or if members in the same class can look very different or if member belonging to different classes share the same

features. Thus, a most challenging problem will be to how to recognize generic objects on a topographic map.

6. In the process of human based topographic map understanding, recognizing something inside the map, i.e. symbol/object understanding includes checking the retinal image against experimental template held in long-term memory. Also, human visual understanding does not rely purely on temple matching or syntactic pattern matching. Next, the human decision has not always crisp in nature, may have fuzziness which creates challenges in achieving intelligence to a topographic map understanding system with a structural framework of knowledge and ambiguity in reasoning.
7. Human topographic map understanding includes legend understanding as a prerequisite but generates rigid knowledge or rule set about legends. However, the emulsion of an analytical model which has to adapt changing information from the topographic map needs to be researched.

Thus, the absence of efficient integral solutions for the map analysis and understanding of topographic maps on a medium scale (1: 10,000 - 1: 50,000) and their relevance to geographic application motivates to develop the automated topographic map understanding method.

# CHAPTER 3
# BACKGROUND THEORY AND VALIDATION METHODS

## 3.1 INTRODUCTION

An appropriate automated understanding model is required to interpret and extract geolocation based layer information from the Indian Topographic map. The geographic information portrayed on topographic maps is complex and crowded with high information density still human is excellent in reading a topographic map. The conceptualization of problem in the recurrent area has been done by defining a problem of information extraction and acquisition from topographic map through the integration of human and machine understanding. The overall objectives of this chapter are to explore basic theory and relevant techniques which have to be integrated into the development of human based map understanding systems. The development of the legend understanding module has been prerequisite which will enable the system to acquire initial knowledge regarding map legends or map specification.

The human mentation process of object recognition has been based on color, structure/shape, and correlation which results in a complete understanding of the object. Human understanding process possesses nonlinear and adaptive nature as well as partial truths and vagueness that can be anticipated in human understanding very easily. Hence, to emulate human understanding of map, the basic techniques which have been parallel to human understanding such as image processing techniques to process legend and map, segmentation methods to separate map layers, the feature extraction of map objects and their numerical measurement methods which describe map object, Pattern recognition methods for classification of map objects, Fuzzy system to extract rules from initial feature description of map legends, soft computation technique to make system to learn the feature based rules comprising map object's semantic meaning assignment, adaptive methods to make system robust to match feature description of new or unseen map objects against learnt knowledge have been studied and explored. Also, system validation has been critical in image understanding domain. Therefore, it has been necessary to study and demonstrate methods to critically validate the completeness and correctness of the system.

A brief discussion of the theoretical basis for the understanding phenomenon and the generalized approaches towards the map understanding problem has been presented in this chapter. In section 3.2 human understanding has been discussed. Section 3.3 provides a brief overview of human understanding of topographic maps. Section 3.4 describes the human mentation processes for topographic map image pre-processing and segmentation. In sub-section 3.4.1, Image pre-processing and segmentation have been explained. Section 3.4.2 provides feature extraction and measurement operations. Partial truth and vagueness handling have been described in subsection 3.4.3. The soft computational techniques have been discussed in sub-section 3.4.4. The inference system and their parameter adjustment have been provided in sub-section 3.4.5 and their subsection. Section 3.5 provides a detailed study of validation and accuracy assessment methods to evaluate the system applicability to the map understanding domain. In the context of Section 3.6, discussion of the significance of the mentioned approaches and techniques towards the development of an automated topographic map understanding system has been provided.

## 3.2 HUMAN UNDERSTANDING

The human understanding process can be defined as the method comprising of experience, insight, and judgment to conceive the idea of being. The analytical model of human understanding may consist of a sequence of processes. Receptors of the retina receive light from objects in the physiological operation of the eye. They have a responsibility to transform and reduce information from light into electrical impulses by neurons in the brain. It initiates thought processing which captures representative characteristics of an object. In the process of visually recognizing objects, the retinal image has been correlated with that in memory representation [216] and if a closest match has been found then it creates understanding about the object as seen or unseen and also adapts knowledge about it. Thus, human understanding has been based on previous knowledge and often results in interpretation or disclosing the meaning of the concept (i.e. high-level description). The basic block diagram of the human understanding model has been shown in Figure 3.1.

For making a machine understand topographic map requires integrating different aspects of understanding to provide a suitable model that can be approached using scientific methods. However, such analytical model in the computer can approximate the human understanding phenomenon to some degree. It has not been possible to construct such a complete model in the computer, but from the definition of the model, it has been easier to infer. It has been presupposed that the human-based understanding would be taken as an effective tool for information acquisition and extraction from Topographic map and for understanding topographic map objects.

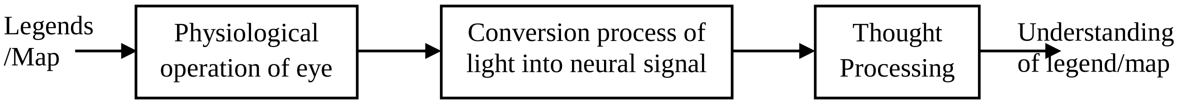



***Figure 3.1 Schematic diagram of the human visual understanding system [216]***

## 3.3 HUMAN UNDERSTANDING OF TOPOGRAPHIC MAP

Reading Topographic Maps starts with understanding the legends set first. Preliminary to human map understanding process, the legend set has to be accurately studied and decomposed into its different components and parameters. Interpreting the objects/symbols on a map would be the second step in using topographic maps. Map objects may be represented geometrically by points, lines, or areas, however, legends act as a key to read a map. The legends encoded in legends set gives information about the map object which has been actually present on the actual map. The appearance of map object may vary based on their size and location. The colors of the map object usually denotes the similar category of information and shape indicates the specific map objects belong to that category. For example, brown color denotes map objects of hypsography category or contour related information, blue color has been assigned to hydrographical category. Locality name and some map objects have been shown as a string of characters in a color corresponding to the type of object. Many objects have been identified by labels, such as administrative or local names. All the map objects and their color and shape specification have been encoded within a legend in legend set.

A fundamental of human map understanding would be to read the map legend to locate, and recognize map objects in the actual topographic map. Legend reading comprises preprocessing of legends, pattern recognition, and shape analysis. Human map reader or expert possesses a skill to read and understand changes in map object's representation in actual map. They have the ability to get the correct level of semantic knowledge (description) about all geographic objects present in the map and encoded in legend set. The physiological operation of the eye receives light from legend and transforms them into electrical signals by neurons in the brain. It identifies the shape and structure as well as it measures representative characteristics of a legend. The semantic meaning associated with that legend would be stored as a category or instance name in the memory. In the process of reading a topographic map, the retinal image has been processed and measured with biological phenomena. The obtained representation of perceived object has been correlated with that in memory representation/storage [107] and if a closest match has been found then creates understanding about the map object as seen object. It also adapts and updates understanding about an object by binding the semantic meaning with it.

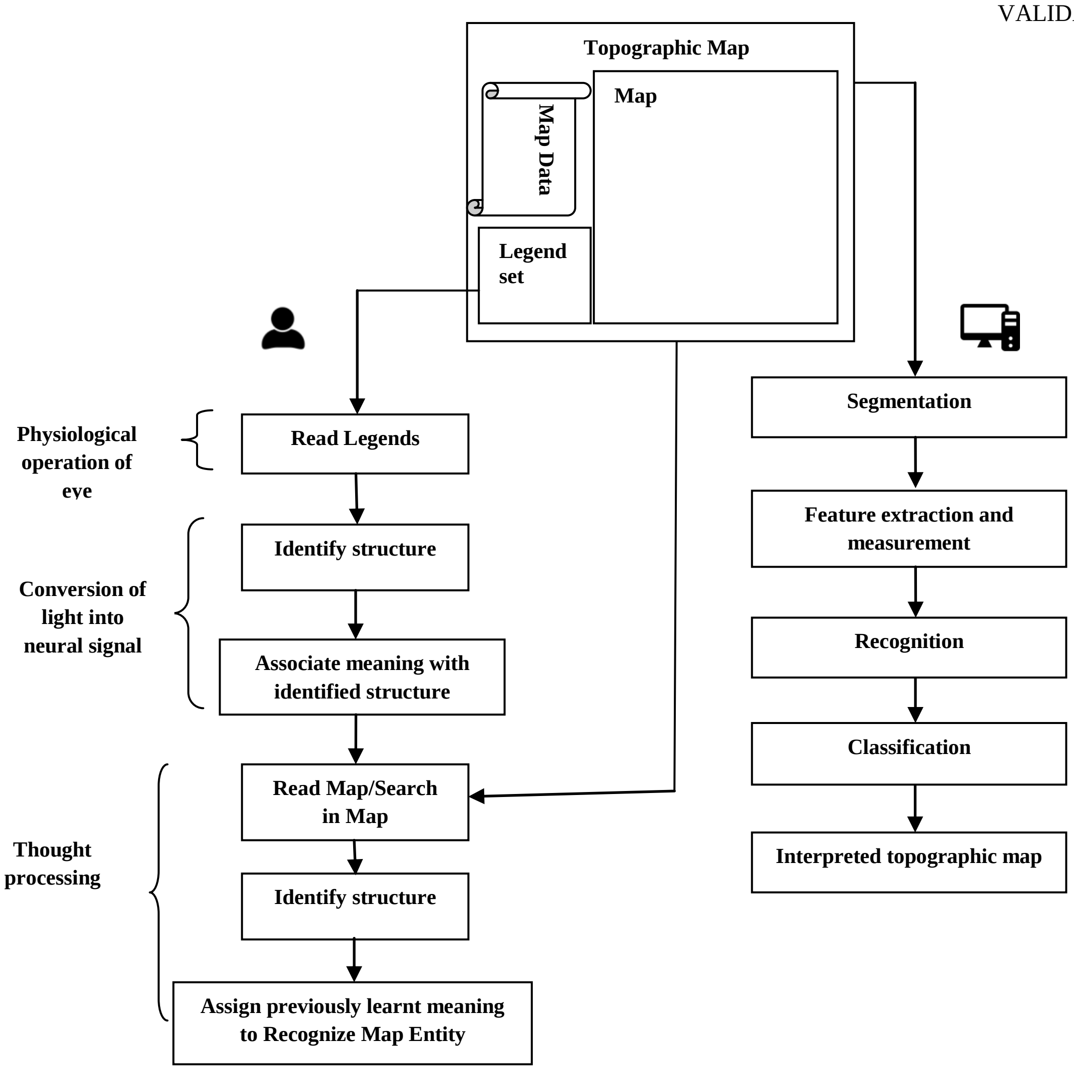



***Figure 3.2 Architectural Framework for Machine map understanding in comparison with Human/Manual map understanding***

Thus, human map understanding has based on legend knowledge and often results in the interpretation of map objects by assigning the semantic meaning given in legend set to the map object. Architectural Framework for Human/Manual map understanding and machine map understanding has been shown in Figure 3.2. It illustrates the human map understanding steps and basic operations towards machine understanding. In the context of a topographic map, the human extracts characteristic features and combines information from different attributes to find objects, distinguish background surfaces. In machine understanding, feature extraction method exhibits a hierarchical process which measures the local features that combine progressively to form more complex descriptions of an object's shape and other structure primitives. The characteristics of a shape such as eccentricity, solidity describe shape profile and may be used for interpretation of topographic map image. In human based understanding, to find correspondence between recognized object or its pattern, human uses correlation theory which is an innate ability inside them. Machine understanding involves pattern recognition may be based on template matching and feature based matching. The emulation of the correlation theory of brain can be implemented in a machine using adaptive perceptrons. Thus, integration of human understanding and machine understanding to recognize patterns of topographic map objects and to produce respective understanding along with geolocation data has been a significant task. The basic theory behind the use of various operations towards map understanding has been provided in the following sections.

## 3.4 HUMAN MENTATION

Topographic map objects representing different map entities in an Indian topographic map have typical geometrical appearances. In order to interpret object on the map, it has been necessary to recognize it by patterns or shape possesses a similar resemblance to the process of human based map reading. In human being, pattern recognition has been done by identifying a stimulus and recognizing a correspondence between a stimulus and information in permanent memory. In human, the key to recognition consists of color, structure or shape. The recognition process is accomplished with incomplete or ambiguous information also. Many variations on a pattern of the same object may be successfully recognized as the same "object" or class of objects. Basically, there have been three theories in pattern recognition [242, 285] as 1. Theory of Template; 2. The theory of Prototype and 3. Theory of Feature.

The theory of template comprising of three assumptions which have been given below:

1) Consideration of Templates in the brain as mental stencils of the object.
2) Comparison of incoming pattern with the stored representation.
3) Largest overlap determines the identity.

Template based model has been suffering due to the orientation and size variance and its sensitivity towards the noise. In template matching, the test image has to be matched against the candidate image using similarity measure. However, variation in orientation, the interconnectedness of topographic map entities often generates distortion in templates. Template matching along with ANN has been used in preliminary research work done by authors [220] and has obtained an acceptable recognition rate for the small parts of the topographic map of size 128 by 128. Unfortunately, training of the ANN with distorted candidate images had not been proved successful in managing with a computation of vague similarity.

The theory of the prototype has been based on a few assumptions which have been provided below:

1. Comprising matching of prototypes based on abstract characteristics of individual objects in one category.

2. The prototype can be considered as an attribute of objects which identifies them under a single category.
3. Once incoming information matches best with a specific prototype in the brain, then information can be assigned and recognized under the category of that prototype.

Only top-down processing has been possible for prototype matching.

The theory of feature has been based on basic assumptions:

1. Representation of past inputs in terms of a list of features.
2. Current inputs have divided or measured into a small list of features.
3. Most similar feature list to the input determines the identity.

The feature-based model has been more natural to map understanding problem. The map object has to be described in terms of small sets of simple shape features. The shape is a vital visual feature of an image so as attracts more attention for searching the image. Several shape representation and description techniques have been reported in the literature. As discussed above, several theoretical models have been presented using the modern cognitive psychology of Human's pattern recognition, such as template-based model, prototype-based model, and feature-based model. Some of these models have been augmented by the artificial intelligence (AI). As for the object understanding purpose feature extraction, analysis, and information integration have been needed, so the models based on features have been provided with the learning capability. But in a feature based model, different patterns may represent by same features which make the recognition more difficult. However, relatively the feature-based model provides good flexibility in discriminating different objects as well as in groups same objects [285]. In human, pattern recognition has been performed on distinct features or feature analysis ,which has been based on the assumption that incoming stimuli consist of combinations of the basic features of objects; The features which include horizontal lines, vertical lines, diagonals, branches, end points, curves, etc. have been sufficient to make discriminations based on a small number of characteristics of stimuli distinctive feature stored in memory [107]. Agosto et al. [11] have developed a geometric approach for reconstruction image.

Unlike the machine, thinking and understanding activity of the human brain has based upon the relative grades of the information obtained by the natural sensory system. While the mathematical tools, deterministic/probabilistic, have been based upon an absolute measure of information. The information acquired in the form of relative grades by natural sensors while the machine is acquired in the form of absolute values. The theory of fuzzy logic has been based upon the relatively graded membership, and so it has the ability to model a function of the mentation process. The fuzzy set theory in the pattern recognition has been suggested in [55, 211] and they have provided significance of many factors like representing input linguistic form for processing, how to represent missing and vague information using membership values, and generation of rules, and description of relations among fuzzy subsets. An automated map understanding system has required analyzing the object's pattern may be in the context of shape feature, or any other and to decide object exists within a map image is of same semantic meaning which has been assigned to the previous input pattern. In knowledge base system, an expert provides [171] domain knowledge to enhance the detection. But in topographic map understanding problem, the type of information that a knowledge base can represent, and infer, cannot be handled by fuzzy grammars. However, an approach consisting of a fuzzy neural network with the adaptive capability seems to be promising to employ due to the resemblance with human mentation. Hence, to emulate human mentation in topographic map understanding, it has been necessary to define object representation and recognition methods as a representative medium.

### 3.4.1 Image Preprocessing and Segmentation

The Indian topographic map is complex map consisting of numerous complex map objects represented by objects which convey meaningful information as provided in legend set. Map objects may be heavily interconnected and overlapped by other map objects. This characteristic exhibits an interesting challenge for automated recognition and understanding of topographic maps. The image processing technique needs to be applied to deal with the complexity of the map. Hence, image processing has been the first step for the correct level of image understanding and pattern recognition. Figure 3.3 illustrates that image processing can be divided into three steps- Image Pre-processing (Low Level), Image Analysis (middle level) and image understanding (high level) processing from pixels to symbols and low-level semantics to a higher level of semantic description. Preprocessing of map image would be very essential to deal with the difficulty of noise and overlapping of objects. Thus, for the ultimate result of recognition and understanding, map preprocessing and segmentation has to be done effectively. Image segmentation consists of a process of dividing an image into different regions or entities based on some common criteria. Image segmentation performance relies on noise reduction, enhancement of the input image. After image processing operation, the enhanced input image has to be described with object regions using common objects for higher level tasks.

Filter plays an important role in image processing. Spatial filtering process deals with an image based on convolution masks. The noise removal, edge detection and several enhancements require the use of masks. The average filter would be one of the most important approaches for creating. Image smoothing defines image-to-image transformation [110, 111, 135, 245, 248, 257] which has to be designed to smoothen topographic map by reducing the pixel-to-pixel variation at the boundary or where abrupt variation observed.

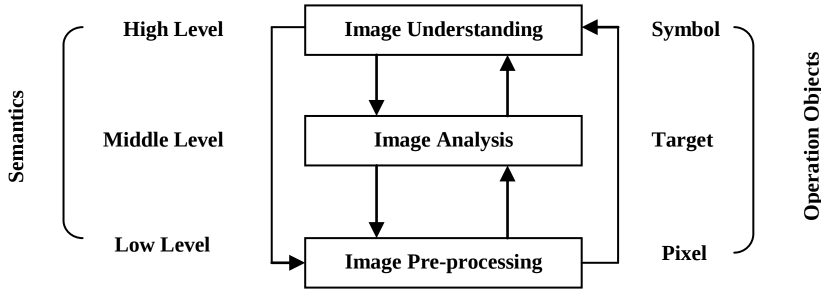



***Figure 3.3 Image processing Model [110]***

Smoothing has been accomplished by employing an average mask that measures a weighted sum of gray levels and replaces the center pixel with that gray level. In the current problem, the topographic map has blurred effect at intersected object boundaries and its brightness may be preserved as the mask coefficients that would return all positive and result in one. The mean filtering, most basic smoothing filters apply a convolution operation as the mask and moves across the image.

Purkait and Chanda et al. [246] have proposed image reconstruction algorithm to remove blurring effect and noise through Bregman iterations and using edge-preserving regularization method.

The mean filter would be effective in the topographic map as variations on the mean filter possesses threshold averaging [256], wherein smoothing has been applicable for the condition where the center pixel gray level changes due to the difference between its original value and the average value. This would cause the noise that has to be smoothed without blurring effect in map detail. Smoothing filter has been an important tool in blurring and noise removal. Thresholding method would be based on characteristics of the map [151]. Based on a correct threshold (T), thresholding operation converts a map image into a binary image say, for dividing image pixels into different parts/categories and separating the objects from the background. Any pixel at (x, y) would be assumed as a part of the map foreground object, if its intensity has been larger than or equal to the threshold, i.e., $f(x, y) \geq T$, else pixel belongs to background [25, 116]. Based on the selection of thresholding value, thresholding methods have been divided into two types such as global and local thresholding [346]. The approach is called as global if T is constant else called as local. Global thresholding methods would not do well as the background in topographic map is uneven. However, by using local thresholding, it would be possible to use several thresholds to deal with uneven color [78]. Threshold selection should be typically done manually based on trial and error [228, 233].

For threshold, t, the pixel resided at position (i, j), with gray value $f_{ij}$, has to be allocated to class I if $f_{ij} \le t$ and if the condition is not true, then, the pixel would be allocated to class II. Generally, threshold values can be chosen manually, by using a series of values of $t$ and observing which one fits better at recognizing the interested objects. The single threshold category includes pixels with the same values residing in the range of 0 to $t$, or in the range of ($t$ + 1) to 255, but able to discern as those pixels would not necessary to constitute a single connected component. At low level to high-level image processing approach, thresholding is augmented by dividing the thresholding resultant categories into sub-categories based on the connected component analysis. More than one threshold has to be used in topographic map color layer separation which results in multiple categories or layers. Based on these categories, the code can be assigned to the interval which is defined by RGB or gray index thresholding. Topographic Map consists of foreground objects and background regions represented by 12 and 3 colors respectively. Out of twelve foreground colors, red is having 5 shades and blue is having 3 tones. Hence, the color would be vital key for pattern recognition and map understanding. Hence a combination of color image segmentation and gray level segmentation may become increasingly more useful in a topographic map. Connected-component labeling and weight matrix techniques would facilitate the separation of the isolated symbol from the foreground and provide a gross classification for symbolic and non-symbol objects. In other words, it would be useful to decipher things into symbols and non-symbols or parts not connected to symbols. Similarly, when connected-component labeling would locate regions bounded by lines constituting polygons. As topographic map has been characterized by points, line, and polyline, the color layer separation based on thresholding and connected component labeling would be of great help. As discussed earlier, mathematical morphology operations have been used in [346] to separate symbols. A morphological operation (i.e. transformation) has been an effective method for extracting features and shape from the map. The primary morphological operation includes dilation and erosion. Based on these two operations, more complex morphological operations such as opening, closing, and shape decomposition and measurements can be employed. The fuzzy based techniques for color image segmentation using T2 fuzzy sets have been presented by Saikat and Sil [192, 286] to handle uncertainty at segmentation stage. Biswas and Sil et al. [40] have developed canny edge detection algorithm based on type-2 fuzzy sets. It handles uncertainties by selecting the threshold values for segmentation of the gradient image using Canny's edge detection.

### 3.4.2 Feature Extraction and Measurements

After image processing operation, the processed input image has to be mapped into a numerical description involving object region with some common representative features for the high-level vision tasks. It has been proved that the human approach to processes an image is not using pixel by pixel statistics. Instead, human identifies some key information that would be created through assimilating related pixels together and describe them using some characteristics would result in a feature. Features as a list of descriptions have been known as a feature vector, carrying discriminating information about shape, boundary etc. for identification. Pal [232] has evaluated the performance of a wrapper–filter genetic algorithm (GA) for feature selection. Classification accuracy by a k-nearest neighbor (k-NN) and support vector machine (SVM) have been used as the fitness function.

Shapes have been described by many parameters such as centroid, minor axis, major axis, eccentricity, convexity, solidity, Euler number, shape profiles etc. [238]. The important characteristics of the feature descriptor have been its effectiveness and with low computation complexity. For feature extraction and subsequent measurement, it has been necessary to transform the topographic map image in region-based shape feature vector by performing various morphological operations and connected component labeling [342]. In late 1960, mathematical morphology based on shape, have been started to develop in the image analysis domain. It uses the concept of mathematical set theory for extracting shape attributes of map objects. Very few global approaches consider the shape as a whole and result in a numerical feature vector which has to be used as a feature descriptor. Also, global region based approaches treat the object region as a whole to obtain a shape description which is not rotation invariant [342]. The parts decomposed by region-based structural methods have been used for shape representation and description. The region structural methods have been suffering due to noise and variations. Apart from their complex implementation, region-based methods have been more robust as uses complete shape information; Also, the structural parameters uses orientation as a feature which added another parameter into the system for accommodating rotation invariant [342]. The region based global and structural have been more robust and having the low computation complexity and would be proven to be effective in describing map objects. The feature based learning has been employed in human activity classification system to generate description [270].

### 3.4.3 Partial Truth and Vagueness

A mathematical framework which makes use of fuzzy logic or fuzzy set is called as a fuzzy system. In this context, fuzzily described systems have more significance for map understanding problem domain. Fuzzy systems can be considered as a generalization of interval-valued systems. The previous knowledge and current data obtained through measurements are two information sources to build fuzzy system [27]. The previous knowledge can be of a predicate form or in approximate nature (shape feature set as an input variable and semantic meaning of legend as an output variable), which would be acquired through “legends set understanding subsystem”. In this context, the fuzzy system will act as an expert who derives rules from the legend prior knowledge [59]. The structure of fuzzy system can be selected based on the following criteria:

1. Input and output variable: For the Sugeno Fuzzy model, the pair ($n_y, n_u$), defines the number of input feature vector and target output using $n_y$ and $n_u$, respectively. Prior knowledge provides insight into the behavior and type of system modeling. On the basis of legend understanding subsystem, initial fuzzy inference system would be designed to extract rules by mapping input feature vector and output legend's description/meaning.
2. The structure of the rules: This option involves the model type (linguistic, singleton (Relational), Takagi, Sugeno) and the antecedent form based on the purpose of design and the type knowledge available. Sugeno has been more suitable for the topographic map understanding purpose as it does not require output membership function and defuzzification method. Also, Sugeno can be easily augmented with learning capability of the adaptive neural network. The Sugeno FIS has been fairly like to that of Mamdani FIS. The main difference is that by clipping an output membership function feature-based, the output result is not determined. In reality, the output membership function is absent in Sugeno FIS. As an alternative, the output number is determined by multiplying each input by a constant and then adding up. This has been reported in Figure 3.6. In this example, Rule strength has been referred as the degree of applicability, while the output as "action". Also, there has only a "resulting action" which is the combination of the strengths of the rule (degree of applicability) and the outputs (actions).
3. Membership function, their count, and type. This is an important design aspect of FIS. It determines the level of detail or how fine input data is quantized. The course quantization of input data decreases the accuracy of the system. Again, the problem domain or details of previous knowledge determine the number of membership functions. The number and type of membership functions for legend/map object recognition can be set on the basis of trial and error.

4. Inference methods, conjunction operators, defuzzification method. These aspects have been restricted by the fuzzy model (Linguistic, Relational, Sugeno). It has been required to facilitate data-driven fuzzy model to learn map objects using differentiable operators like product or sum. Once an FIS structure has been finalized, the performance can be enhanced by adjusting parameter values.

For map understanding, map, object data would be available as map understanding process progresses or region of interest selected to obtain the representative feature vector and relevant data. The building of initial rule extraction or knowledge creation from legend's feature data needs fuzzy logic and reasoning. Also, conventional learning from the field of neural networks has been important. The acquisition or tuning of fuzzy models by means of data has been usually called as a data-driven fuzzy model. For integration of knowledge and data in fuzzy model, two basic approaches have been described in a fuzzy model:

1. No prior knowledge has been used in formulating the rules, and a fuzzy model has been built from data. The behavior of the system is presented by extracting rules and membership functions. Based on the knowledge, an expert can analyze the information and accordingly modify the rules or supply new ones and for obtaining additional information can design new experiments.
2. The expert knowledge has to be converted into a knowledge structure consisting of a set of if– then rules. The structural parameters like membership functions, consequent parameters can be adjusted based on input-output data. A fuzzy model similar to artificial neural networks being a layered structure, for learning algorithms have to be applied. This approach has been called as neuro-fuzzy modeling [138, 139]. But, if prior knowledge would be generated by the system based on reference data, would add novel experience in designing the inference model for map understanding which will scratch rules from legend data created by the system by itself.

## 3.5 SOFT COMPUTATION TECHNIQUES

Soft computing techniques employ fuzzy logic, ANN etc. in a complimentary manner. Fuzzy logic gives a definite conclusion based upon uncertain, missing or vague input information [352, 353]. A fuzzy system which employs fuzzy logic formulated as a set of membership functions, a number of rules. The rule consists of two parts; antecedent which describes to what degree the fuzzy input variables exhibits membership value and consequent assigns a membership function to each output variable [335, 336]. An Artificial Neural Network (ANN) exhibits paradigm inspired by human brain [147, 255, 256]. Novel structure, activity rule and learning rule are the key elements of this concept, which has been composed of a vast number of highly interconnected information processing units i.e. neurons. The activity rule defines how the activity or behavior of neuron changes in response to each other. The learning rule defines the way in which weight changes with time. A hybrid model can be formed by integrating FL and ANN together to combine their inherent capabilities. The ANFIS hybrid model, developed in the early 1990s [138] was based on Takagi–Sugeno fuzzy inference system. As the integration of neural networks and fuzzy logic principles has been observed in the techniques, shows the ability for inheriting the potential of both in a single framework. Its inference system consists of a collection of fuzzy IF–THEN rules that exhibit ability to learn to approximate nonlinear functions like human mentation. The pattern recognition model has been developed by Chakraborty et al. [56] based on artificial neural networks (ie, a mathematical model that tries to simulate the structure and/or functional aspects of biologic neural networks for classification of asthma patients. Ray and Chaira [252] have investigated background work in neuro-fuzzy computing in remote sensing.

Humanly is efficient in reading and in understanding complex and imprecise topographic map data. In this study, human based map understanding has been considered as an ideal analytical role model for developing automated map understanding solution. However, soft computing in which, the human mind is role model shows the ability to handle vague and imprecise data to make decisions. Hence, in the present study, soft computing techniques have to be employed for a better solution. To recognize map object as a specific class or instance, the system must learn from legend set data samples or by means of examples which are unseen to the system. Once the system learns the pattern in map object features as well as maps input feature set to output description, its generalization capability has to be checked. During validation, the system may find the output (map object description) for similar feature vectors of the same object class that would not be used in explicit training. This, in turn, results in a high degree of fault tolerance against input feature vector which may vary due to occlusion or intersection. Learning from scratch would not yield good ANN model, instead, it has been preferred to learn rules generated by initial knowledge.

A fuzzy inference system (FIS) has been defined as a system that maps object inputs to output classes by using fuzzy set theory. The first layer nodes calculate the membership degree of the shape feature input vectors in the previous part. The nodes in the second layer consist of conjunction operator. Next, the normalization node (N) calculates ratio of the firing strength of $i^{th}$ rule to the sum of the firing strength of all rules. By applying membership functions, e.g. Gaussian functions, parameters have been updated based on gradient descent learning algorithms, such as back-propagation [321]. These are used for fine tuning of a fuzzy model for the available legend data set in order to optimize its generalized ability.

The Sugeno FIS lacks the ability to determine the coefficients or parameters. Also, the Sugeno generates only crisp outputs. The Sugeno FIS can be optimized automatically by some algorithms like ANFIS, Genetic algorithm, etc. The adaptive Neuro-fuzzy inference system (ANFIS), adapts the parameters of the FIS using neural networks. The design process of ANFIS model has been based on clustering of a training set of numerical samples. The adaptive-network-based fuzzy inference system (ANFIS) uses parameter identification and optimization through learning and training algorithms combining the gradient descent and a least-squares estimation method. The basic steps towards the use ANFIS includes:

1. The design of a Sugeno FIS for the map object classification problem.
2. Optimization of the FIS given actual feature input data.
3. Assignment of training and testing matrices composed of inputs and the desired output corresponding to those inputs.
4. Execute the ANFIS program, on the object feature training data.
5. Test the results, based on testing data.
6. Increase training data by adding feature data of those objects which are wrongly recognized.

Once scarcity of training data has been available then train the system using offline learning.

Thus, ANFIS acts as the best tradeoff between neural and fuzzy systems, constituting smoothness, due to the Fuzzy system interpolation and adaptability due to the offline learning.

### 3.5.1 Inference System Design

The design of a fuzzy model for initial knowledge heavily depends on the extent and quality of the available training data. In the next subsection, the important steps and options in the construction of fuzzy models and the important techniques for extracting or fine tuning fuzzy models have been described in short.

#### 3.5.1.1 Acquisition/Tuning of fuzzy models

If a set of N input-output data pairs $f(x_i, y_i)\{i = 1, 2, ..., N\}$ is available. The $x_i \in R^p$ are input vectors and $y_i$ are output scalars. The $x_i \in R^{NXp}$, a matrix having the vectors $x_k^T$ in its rows, and $y \in R^N$ a vector containing the outputs $y_k$ has been reported in [22ch3]

$$X = \{x_1, x_2, ..., x_n\};\ Y = \{y_1, y_2, ..., y_n\} \qquad \text{Eq.(3.1)}$$

In this technique, the antecedent variables have been simply partitioned into a specified number of equally spaced and shaped membership functions. The rule base has been then established for covering all combinations of antecedent terms and for estimating consequent parameters, least-squares method has been used. This approach has a disadvantage as the number of rules in the model increases fast. The nonlinearity of the system due to unavailability of knowledge partitioned all antecedent variables uniformly. Yet, the system behavior complexity would not be uniform. For efficient model, the selection of membership function has been important for capturing the non-uniform behavior of the system. In topographic map understanding problem, map, object has to describe by input feature vector consisting of 8 shape feature and one output has been expected, which is crisp in nature giving the semantic meaning of the corresponding object.

Here, a set of $N$ can be specified as input-output data pairs $f(x_i, y_j)\{i=1,2,...,8;\ j=1\}$ are available. They $x_i \in R^p$ are input vectors and $y_i$ are output scalars. The matrix having the vectors $x_k^T$ in its rows and $y \in R$ a vector containing the outputs $y^T$. By rewriting Eq. 3.1, following equation, has been obtained.

$X = \{x_1, x_2, ..., x_n\}^T$ ; $Y = \{(y)\}^T$

A Sugeno type of fuzzy system may have the rule base, for map object classification as given below:

1. $R^i \in x_i$ is $A_1^i$ and $x_2$ is $A_2^i$.....and $x_n$ is $A_m^i$, then

   $$y^i = a_0 + a_1^i x_1 + ... + a_n^i x_n \qquad \text{Eq.(3.2)}$$

   where, $R^i$ denotes $i^{th}$ fuzzy rule; $A_i^1, A_1^2, ...., A_m^i; B^i$ are fuzzy membership function associated with it; $x_j$ is the input; $y^i$ is the polynomial in the input variables.

   When $y^i$ is a first order polynomial, the resulting fuzzy inference system has been called as a first-order Sugeno fuzzy model [142]. For topographic map symbol understanding, to avoid defuzzification due to highly variable input feature, zero-order Sugeno model can be useful with f as constant. The overall output should be obtained by weighted average, as each rule has crisp output. The parameter optimization can be carried out based on nonlinear optimization method [212].

2. In evaluating the rules, binary operation *product* (logical *and*) gives the rule premises results in

   $$w_i = \mu_{A_i}(x)\mu_{B_i}(y), i = 1, 2 \qquad \text{Eq.(3.3)}$$

3. Evaluating the implication and the rule consequences gives

   $$f(x,y) = \frac{w_1(x,y) f_1(x,y) + w_2(x,y) f_2(x,y)}{w_1(x,y) w_2(x,y)} \qquad \text{Eq.(3.4)}$$

Or leaving the arguments out

$$f = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \qquad \text{Eq.(3.5)}$$

The weighted average can be rewritten as

$$\overline{w_i} = \frac{w_i}{w_1 + w_2} \qquad \text{Eq.(3.6)}$$

and $f$ can be written as

$$f = \overline{w_1} f_1 + \overline{w_2} f_2 \qquad \text{Eq.(3.7)}$$

The ANFIS network and all computations at each node have been illustrated in Figure 3.4. The Generally, ANFIS consists of 5 layers of neuron and each layer neurons are performing the same function [138, 139].

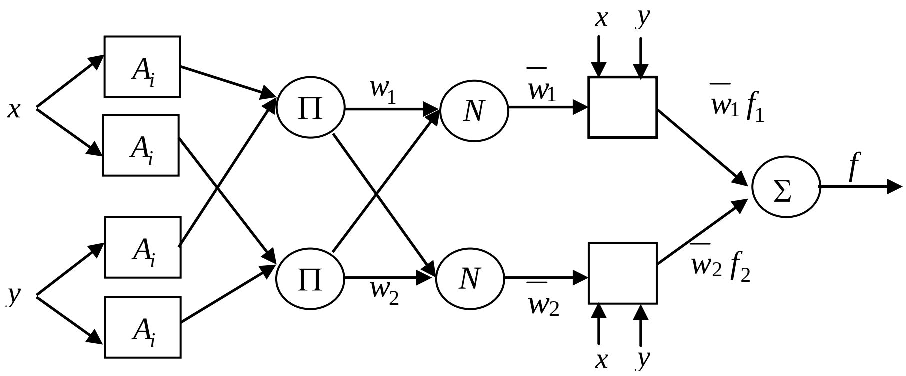



***Figure 3.4 Structure of ANFIS network [139]***

Layer 1 (L1): Each of the neurons generates the membership grades.

Consider, generalized *bell function* as a membership function:

$$\mu(x) = \frac{1}{1 + \left| x - c^{2b} / a \right|} \qquad \text{Eq.(3.8)}$$

where $\{a, b, c\}$ is set of parameters.

The shape of the membership function variables with the values of the parameters. Parameters in this layer are called as *premise parameters*.

Layer 2 (L2): The firing strength of each rule has been calculated using the *min* or *prod* operator. In general, any other fuzzy AND operation can be used.

Layer 3 (L3): The ratios of the rule's firing strength to the sum of all the rules firing strength is calculated. The result is a *normalized firing strength*.

Layer 4 (L4): The nodes calculate a *consequent parameter* function on the layer 3 outputs.

Layer 5 (L5): Single node/neuron present, which performs a summation of all incoming signals and aggregates overall output.

If the premise parameters are fixed, the overall output is a linear combination of the consequent parameters. In symbols, the output $f$ can be written as,

$$f = (\bar{w}_1 x)c_{11} + (\bar{w}_1 y)c_{12} + \bar{w}_1 c_{10} + (\bar{w}_2 x)c_{21} + (\bar{w}_2 y)c_{22} + \bar{w}_2 c_{20} \quad \text{Eq.(3.9)}$$

which is linear in the consequent parameters $c_{ij}$ ($i$ = 1,2; $j$ = 0,1,2). A hybrid algorithm is used to calculate and adjust the consequent parameters $c_{ij}$ in a forward pass and the premise parameters $\{a_i, b_i, c_i\}$ in a backward pass [139]. The network inputs propagate forward until layer 4, where the consequent parameters would be identified by the least-squares method. However, the error propagates backward and the premise parameters would be modified using the gradient descent method.

Mitchell [210] reported the definition of learning as "*A computer program is said to learn from experience E with respect to some class of task T and performance measure P, if its performance at tasks T, as measured by P, improves with experience E*" [96].

Neuro-adaptive learning techniques would solve parameter identification problem of FIS that allows the FIS to map the given input into output map data. In order to deal with map object data, the learning algorithm has to tune all the modifiable parameters, to match the training data. The adaptive neural network has to be trained by a hybrid learning algorithm integrating least square method and gradient descent method. The least squares method identifies the optimal values of the consequent parameter on the layer 4 with premise parameter fixed. Gradient vector determines the error measure of fuzzy inference system in modeling the input/output data for a given set of parameters [139]. Once the gradient vector is determined, then any optimization routine has to be applied so as to correct the parameters for reducing the error measure [149]. The output error used to adapt the premise parameters through a back-propagation algorithm for minimizing the mean square error function calculated by Eq. (3.10). Many researchers [138] confirmed that the hybrid algorithm has high efficiency in training the ANFIS.

$$E_p = \sum_{k-1}^{N(L)} (d_k - x_{l,k})^2 \quad \text{Eq.(3.10)}$$

Where $d_k$ is the desired output and $x_{l,k}$ both for the $k^{th}$ of the $p^{th}$ desired output. The gradient vector is calculated to pass from derivative information backward, i.e. from the output layer to the input layer. In Eq. (3.10) the squared error has to be minimized by least squares estimator (LSE) [301]. Therefore, the hybrid learning algorithm would be applied directly. Thus error calculated at each node propagates backward and used to modify premise parameter by gradient descent, however, node output goes forward until layer 3 where consequent parameters are determined by the least square method.

## 3.6 VALIDATION AND ACCURACY ASSESSMENT TECHNIQUES

System accuracy assessment and validation of the obtained results are important parts to find the relevance of topographic map understanding and information extraction system for practical applications. Many approaches have been present to evaluate the system in the context of several applications. Generally, the evaluation is carried out by comparing the system's interpretation result with the reference data or manually interpreted data [125, 129, 325, 327]. The self-diagnostic test has been carried out and implemented as a part of a road extraction system [128, 326]. An approach for the external evaluation of the extraction results has been demonstrated in [326]. The global framework for evaluating symbol recognition system has been found in [311]. They suggested a generic metric to test the evaluation aspects of the system. First is the number or rate of false positives symbols, completeness and correctness of the system, the second is confidence rate if available, third metric is computation time and the fourth one is scalability, i.e. degradation of recognition rate with an increase in the number of symbols in test area. All these aspects are based on kind of data and kind of symbols extracted. There are several evaluation frameworks have been specified in the relation to kind of symbols and processes in recognition [117, 119, 169].

In the current work, it has been proposed to evaluate two main aspects in the Indian topographic map understanding system: the completeness and the correctness of the system and extent of feature extraction in layers. Accuracy assessment has been critical in map image understanding or map image analysis. To assess the performance of the legend understanding system, the rate of correct recognition based on criteria of manual validation as used in [190] has been used in the thesis.

*Accuracy = (Number of correct legend recognition/Total number of legends )*100*

*Average Accuracy = (Sum of legend recognition result of all topographic map legend sets/Number of a topographic map).*

Manual interpretation has been used as the evaluation criteria for accuracy assessment of the legend understanding subsystem. It has been done by comparing interpretation results of LUS and manual checking of legend set.

To assess the overall performance of map object interpretation and information extraction, the quality measures based on quality error matrix or contingency table viz. Overall completeness, overall correctness and rate of correct recognition discussed in [190], has been appropriate in this thesis.

TP: All instances of map objects which are common in both data sets, REF, and EXT. This number shows correctly interpreted objects;

FP: All instances of map objects which are members of the data set EXT but not included in REF. It shows number of false interpretations;

FN: instances of map objects which are members of the data set REF but not included in EXT. It gives the number of map objects which are not interpreted either correctly or wrongly.

$$Overall\ Completeness = \frac{TP}{TP + FN}$$ Eq.(3.11)

$$Overall\ Correctness = \frac{TP}{TP + FP}$$ Eq. (3.12)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$ Eq. (3.13)

$$Rate\ of\ Correct\ \mathrm{Re}cognition = Average\ of\ \frac{No.of\ correctly\ recognized\ map\ objects}{No.of\ map\ objects} \times 100$$

Eq. (3.14)

*Evaluation Metrics*

Many approaches are present to check the efficiency of the system using several external evaluation and self-diagnosis test [15, 28]. The system performance can be checked by implementing contingency table or confusion matrix as shown in Table 3.1. The evaluation metric curves have been shown in Figure 3.5. The definition of evaluation metrics has been provided below:

Recall (training samples, TR) = $\frac{w}{n_1}$ and

Recall (testing samples, TS) = $\frac{w}{n_1}$,

where $n_1$ is equal to $(w + x)$. Here, $x$ is relevant, but not recognized symbols.

Precision (training samples, TR) = $\frac{w}{n_2}$ and

Precision (testing samples, TS) = $\frac{w}{n2}$,

where $n_2$ is equal to $(w + y)$.

Here, $y$ is recognized, but not relevant symbols. Table 3.1 describes evaluation metrics of the proposed system of symbols.

Overall percentage accuracy i.e. $\frac{w}{N}$ (for both training and testing samples) may be computed.

For the system validation, the 5 topographic maps from OSM Geotiff have been used. To evaluate the average performance of ITMUS system, Precision-Recall curve, and Receiver Operating Characteristic curve have to be plotted. In Figure 3.6, the ROC space characterized by the False Positive Rate (FPR) i.e. the false alarm rate and True Positive Rate (TPR) have been shown on x- and y-axis respectively. Accuracy is measured by the area under the curve. The area measures ability to discriminate, and good-bad are a generic point system to classify the accuracy. If area measures in between 0.80-0.90, then accuracy is good. If area measures between 0.60-.070 then accuracy is poor. The FPR, TPR, and accuracy show the performance of the system [264]. The FPR represents the number of non-relevant objects that are interpreted as relevant. The TPR gives the number of relevant objects that are correctly labeled. False Positive Rate, True Positive Rate, and Area under Curve (AUC) has to be plotted to see the performance of the system.

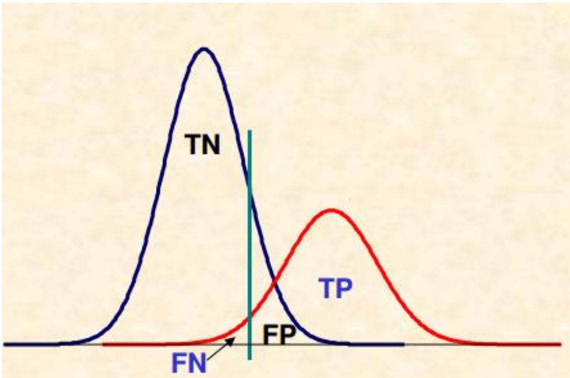



***Figure 3.5 Evaluation metrics***

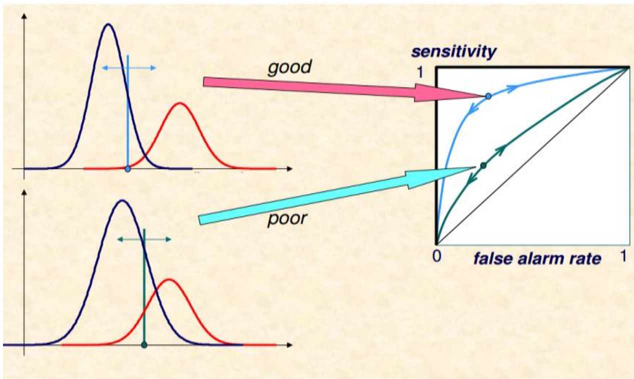



***Figure 3.6 Receiver Operating Characteristics (ROC)***

To measure the efficiency in terms of retrieval accuracy and recognition rate, V-fold cross validation technique have been demonstrated by [15, 172], has been established in this thesis. The sample images have to group into 5 folds or sets. In 5-fold cross-validation, the topographic map region images must be divided into 5 equal sized sample sets. Of the 5 sample sets, one sample has to retain the validation data for testing the model, and the remaining 4 sample sets have to be used as training data. The cross-validation process would be repeated 5 times, till each of 5 sample set has been used exactly once as the validation data. The 5 types of results from the 5 iterations have been averaged to calculate recognition rate. The advantage of 5 fold cross validation over other methods would be that it is possible to train the system with all data in hand in several iterations and observe results for both training and validation. The process repeats and requires 5 iterations to give an overall success rate.

***Table 3.1 Contingency table for accuracy assessment [15]***

| | **Relevant / Correct** | **Not Relevant / Not Correct** | | |
|---|---|---|---|---|
| **Recognized** | $w$ : TR$^{*}$; TS$^{**}$ {TP-Hit} | y : TR; TS {FP} Type-I Error | Positive predictive value | $w/(w+y)$ |
| **Not Recognized** | x: TR; TS {FN- Miss} Type-II Error | z: TR; TS {TN-Correct Rejection} | Negative predictive value | $z/(z+x)$ |
| | Sensitivity | Specificity | Accuracy | |
| | $w/(w+x)$ | $z/(y+z)$ | $= w+z/(w+y+x+z)$ | |

$^{*}$**TR:** for training samples, $^{**}$**TS:** for testing samples

The evaluation of the understanding system can also be possible based on statistical measurements [26, 35]. These statistical measurements include root mean square error (RMSE), percentage root mean square error (%RMSE), accuracy and Mean absolute Error (MAE) (as given in Eq. 3.11, 3.12, 3.13 and 3.14). The Legend and map object interpretation from both LU systems and MU system has been compared to the Conventional signs and metadata prepared by the Survey of India respectively. The RMSE and %RMSE and the accuracy have been presented in Eq. (3.11) and Eq. (3.12), respectively. The performances of the developed system have to be evaluated using statistical performance evaluation criteria.

The RMSE, %RMSE, Accuracy and Mean absolute error (MAE) have been defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[P(x_i) - M(x_i)]^2} \qquad \text{Eq. (3.11)}$$

$$\%RMSE = RMSC / mean(x) \qquad \text{Eq. (3.12)}$$

$$Accuracy = \frac{Number\ of\ correct\ recognition\ of\ objects}{Number\ of\ object\ instances\ present} \qquad \text{Eq. (3.13)}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} P(x_i) - M(x_i) \qquad \text{Eq. (3.14)}$$

where $P(x_i)$ represents the $i^{th}$ predicted, $M(x_i)$ is the actual value of feature vector $i$, $M$ is the mean of actual values, and $n$ is the data index.The reference data include the occurrences of real objects on the ground are recognized as such, while the map understanding system accuracy refers to the measure which provides that an object recognized as a certain object type in the map is really of this type based on the reference data. Thus the quantitative results are obtained by comparing the reference data with the classified objects using ANFIS as classifiers.

The goodness of the classifier used in the topographic map understanding system can be evaluated using $R^2$ values. It can be defined as the Correlation coefficient ($R$) which gives the determination of the relation between measured and model predicted symbols in training or testing stage. The correlation coefficient is a measure to denote how well trends in the predicted values follow trends in actual values [39] i.e. it may be used as a measure of how well the predicted values from a system fit with the topographic map data. It is expressed as in Eq. 3.15 as,

$$R = \frac{\sum_{j=1}^{n}\{(Y_j - \bar{Y})(\bar{\bar{Y}}_j - \bar{\bar{\bar{Y}}})\}}{\left[\sum_{j=1}^{n}\{(Y_j - \bar{Y})^2 \sum_{j=1}^{n}(\bar{\bar{Y}}_j - \bar{\bar{\bar{Y}}})\}\right]^{\frac{1}{2}}} \qquad \text{Eq. (3.15)}$$

where, $\bar{Y}$ and $\bar{\bar{\bar{Y}}}$ are mean of actual and predicted values.

The coefficient of efficiency, $R^2$ is used to assess the accuracy of prediction of a model.

$$R^2 = 1 - \frac{\left[\sum_{j=1}^{n}(\bar{\bar{Y}}_j - \bar{\bar{\bar{Y}}})\right]^2}{\left[\sum_{j=1}^{n}\{Y_j - \sum_{j=1}^{n}(Y_j - \bar{\bar{\bar{Y}}})\}\right]^2} \qquad \text{Eq. (3.16)}$$

If the N number of ANFIS models has been developed with topographic map object features as input and object semantic/meaning ($U$) as output for 53C7, 53F6, 53F7, 53F11, 53K1 territory in India. The individual model has to be trained independently for a different number of their corresponding training samples. Out of N number of total models 9 models has to be selected which gets trained on any number of training samples (Refer Table 5.19). Based on correlation coefficient ($R$) and *RMSE*, the nine ANFIS models have to be selected to incorporate them into ITMUS. The output understanding about map object $U_t$ where t is number of objects to be recognized by that model was mapped with input feature with i.e. $F_1$, $F_{2}, \dots, F_8$ etc. and the previous learned features i.e. $F_{1-p}, F_{2-p}, \dots, F_{8-p}$ etc. Each model would be trained, tested and validated using the input data from the Indian topographic map. Nine best models for nine categories, each includes a set of topographic map objects having similar resemblance would be selected out of all the developed models used for modeling of the five OSM Geotiff topographic map data sheets.

It is important to check the acceptability as well as the ability of a classifier. The root mean square error is one of the criteria to compare the performance of two models when the same data are used for the development. However, the correlation coefficient as a measure provides the degree of correlation between the actual and predicted values. Also, Coefficient of efficiency depends on upon the variance of actual/measured values [148]. These performance indices have been used for evaluating the quantitative evaluation of ANFIS models during the testing period. To produce the effective system, the performance indicators have to be observed during the development of the system. To judge the predictive capability of the developed system, Correlation Coefficient, Mean Square Error (MSE), can be used.

To independently assess the overall performance of the Map understanding subsystem, the "count of errors" approach used in [83] and a comparison between automatic and manual approach given in [190] has been appropriate and used in this thesis. The following types of errors serve as an objective measure for the evaluation of the adopted methodology [97].

(i) Substitution errors—a relevant label is assigned incorrectly to a relevant map symbol.

(ii) Deletion errors—a map symbol is not interpreted.

(iii) Insertion errors—a non-relevant symbol is classified as relevant.

Using the above errors, the results of the system can be analyzed by plotting error rate.

The percentage of correct interpretation and quality measures such as completeness, correctness, correct recognition have been used for accuracy assessment and system validation. The error matrix gives the number of map objects which have not been interpreted either correctly or wrongly [83, 190, 311]. The three measures have to be deduced from the error matrix as True Positive (TP), False negative FN) and false positive (FP). True positive measures all instances of map objects which have been common in both data sets, INTERPRETED, and REFERENCE. This number would show the correctly interpreted objects; False Positive measures all instances of map objects which are members of the data set INTERPRETED but not included in REFERENCE.

For the assessment of layer, extraction shows that how much extent of objects in each layer is extracted correctly. The map layer extraction, assessment as discussed in [190] has been appropriate for overlay analysis of system generated layer and manually delineated layer to derive a penalty matrix. The value is estimated a misclassification result in terms of the low, medium or high index. The details of the penalty matrix and cost of misclassification have been provided in Appendix II.

### 3.7 DISCUSSION

The goal has been not only to parallel the advances in technologies (e.g., image processing, pattern recognition, feature description and soft computation) but also to be linked to the fact that implementation of automated map understanding methods for the utilization of the contained geographic information in a modern geo-information based information environments (e.g., in a GIS). For this, it has been essential to analyze the architectural requirements of the automated understanding system development by comparing it with the traditional method. However, these methods assume a basic systematic organization, and guide the design parameters, within the scope of the understanding domain only. The design of a successful automated understanding using more abstract and appropriate techniques has been discussed. The use of techniques in relevance to a specific application domain has been checked against its pros and cons. All concepts in map understanding model have been discussed in a technological point of view. The technical concept discussed has been processing of the image, feature extraction, and measurements, partial truth, and vagueness, Inference system design, Soft computation techniques. The image processing provides a good feature description scheme for map object recognition. The image preprocessing, morphological operations and feature based classification will be employed to understand legend set. The FIS has the characteristic to extract rules from initial knowledge. The initial FIS generates rules from initial legend feature sets. The hybrid learning algorithm would improve the quality of if-then rules to describe the input-output behavior of a complex topographic map understanding process. The soft computational techniques would evaluate these rules and fine tune classification parameter until the system becomes well-trained and stable to produce reliable results. These techniques have been useful and appropriate for modeling human mentation for the development of automated map understanding systems. Various validation methods have been provided that would be appropriate for validating map understanding system. The basic theory behind the use of various operations towards map understanding has been provided to form a good platform for the development of the automated map understanding system.

# CHAPTER 4 PROPOSED SYSTEM

## 4.1 INTRODUCTION

Topographic maps are an important source of geographical and geospatial information. Currently, topographic maps are extensively used for development of automated geo-information system including GIS. However, geographical and location information about map object/symbols has not been ready to use in a computer-based system which are demanding geospatial data as an input. The extraction of information from topographic maps is being carried out through the process of manual digitization or semi-automated methods [145, 261]. Because such methods are labor intensive, error prone and slow [190], there is a great need of an appropriate topographic map understanding system capable of extracting geographical and geospatial data/information from the topographic map.

Interpretation of geographical objects/entities from the topographic map is a perplexing task. The algorithms have to deal with varying object representations as well as occluded objects [329]. Advanced pattern recognition algorithms or hybrid approach has to be applied for the acquisition of information from the highly complex topographic map [83, 90]. Some of the approaches have been already developed for the interpretation of topographic map, but the system is not working for whole topographic map analysis and failed to give generalized solution for automatic extraction of information from maps [90, 113, 254]. The inherent difficulty in the topographic map analysis is the complexity which is due to object density and overlapping [94, 190]. However, based on learnt map legends, human being read highly complex, interconnected or overlapped object of topographic map quite easily. An appropriate human based automated understanding model is required to interpret the topographic map which provides a useful output for the development of automated geo-information system.

Geographic information depicted on topographic maps is a complex and crowded in nature with high information density, but still human reads and understands it efficiently. Naive Geography has claimed that maps act as representational and communicating medium for geographic and spatial information, whereas human perceives map in the form of geometric and symbolic information. Both types of information have been relevant for map user [91]. Without symbolic information, i.e. key or legend information, map user has unable to decide what is depicted on the map. Hence, it has been necessary to examine and emulate the way in which human interacts with a topographic map. Computers have been more deliberate, more precise and less prone to exhaustion and error than the human being. The objective of the research has been to simulate the model in which people studying a topographic map, first read the printed legends. Shortly afterward they recognize objects that might not be directly depicted on the map in the same form as found in legends. Still, they perceive it through the formation of their location and shape in nature. Thus the human being gains understanding about the map object by establishing correspondences between object's structure knowledge and formal description adaptively. Hence, an automated map understanding model based on human understanding will be of great help.

To achieve the objective of this research work, automatic machine understanding of Indian topographic maps has been proposed which has been based on the human concepts and human principles of partial truth, vagueness and nonlinear adaptive mechanism. In the following sections of this chapter, the salient features of proposed system have been discussed in Section 4.2 followed by an explanation of proposed system architecture in Section 4.3. The system module description has been given in Section 4.4 along with submodule design. The basic operations of the proposed system have been described with sub module functioning. The system requirement has been described in Section 4.5. The Indian Topographic map data has been described in Section 4.6. The discussion of the chapter is provided in Section 4.7.

## 4.2 SALIENT FEATURES OF THE PROPOSED SYSTEM

The research work has exhibited two ultimate goals of making the system understand the conventional signs from topographic map legend set and generate a description of map contents automatically. Secondly, the goal has been to understand the topographic map and perform color/feature-based layer analysis. The output of the system that may be further used in the Geoinformation based systems likes ARC/INFO GIS for performing geographical tasks in many applications.

The map-making process comprising a cartographic transformation ‘C’ of the geographic data to the topographic map. Ideally, objective consists of the implementation of a system to inverse the transformation 'C' to obtain the original encoded geographic and geospatial information from the topographic map. The act of transformation has been shown in Figure 4.1. On account of the procedure of the interpretation of maps with respect to a map representation theory, the formal knowledge on the map making process has to be acquired and hence it becomes desirable to automate the process of interpretation accordingly. According to the Gestalt principle of human interpretation process, the map reader realizes that simplicity of identification, the similarity in the arrangement, shape, size, similarity in

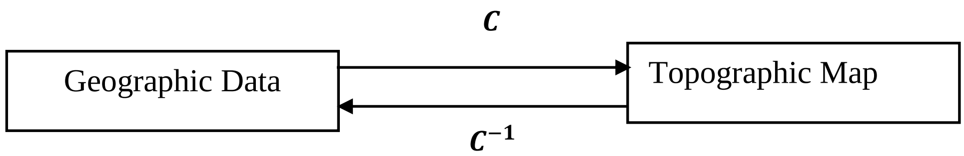



***Figure 4.1 Ideal correspondence between cartographic transformation (C) and Interpretation $C^{-1}$ processes [30]***

geometry, structure, context, common region, topology have been most important factors for interpretation[304].

According to the Gestalt principle, proximity, contrast, connectedness, symmetry, context, orientation, and the likelihood of correct interpretation have been less important. The rated importance of the Gestalt principle for interpretation process has been given in Figure 4.2. From the Gestalt principle has been illustrated by the chart diagram, and on that basis, it has been clear that shape, structure, similar in geometry, the similarity in the arrangement are important factors to recognize or interpret map objects correctly. According to Gestalt Principle, experience, existing knowledge about land use and knowledge about the form and size of objects have been important for extracting land use information from a topographic map [304]. These results confirm that interpretation and understanding process may consist of knowledge-intensive tasks where existing knowledge and knowledge about the form of map objects has been crucial for the inference, and that any understanding system needs to be acquired an exhaustive but precise knowledge and a trained problem solving/inference engine.

## 4.3 PROPOSED SYSTEM ARCHITECTURE

Geographic information presented on topographic maps has complex and crowded information. Map legends consist of sets of graphic signs, whereas map symbols have been dispersed on the map; they have been endowed the task of representing the ground entity. In the topographic map, legends, have been assigned the semantic meaning or description to them and convey the basic rules to building map symbols. Topographic map symbols have been formed according to the rules. But they appear to be connected to other map entities making it complex to find a generalized procedure of searching for map symbols. The identification of humanly acceptable concepts should be the first step towards establishing more realistic understanding models in the machine/computer. Hence the emulation of human learning has been proposed to implement to understand the map symbol. Psychological studies show that humans acquire a great amount of knowledge and analyze an unknown object data based on known objects. Usually, these models can be further improved or generalized, as soon as new objects are available. Thus, the object can be understood as a control loop consisting of learning and interpretation [187, 283]. However, machine learning involves learning by example. In supervised learning, a set of examples is provided with a given output; then the system generates rules to link input and output which turned into classification rules [209].

The hierarchy of topographic map symbols/objects has been shown in Figure 4.3. The proposed system's architecture has required possessing all equivalent operations that exactly takes place in manual map reading from low-level processing to high-level classification, from the training phase to testing phase. It has been illustrated in Figure 4.4 a. In this section, an approach to topographic map understanding starting from legend set understanding based on shape features have been proposed. Learning module has been proposed to evaluate rules from the initial legends structure knowledge that enable the automated interpretation of rasterized topographic maps.

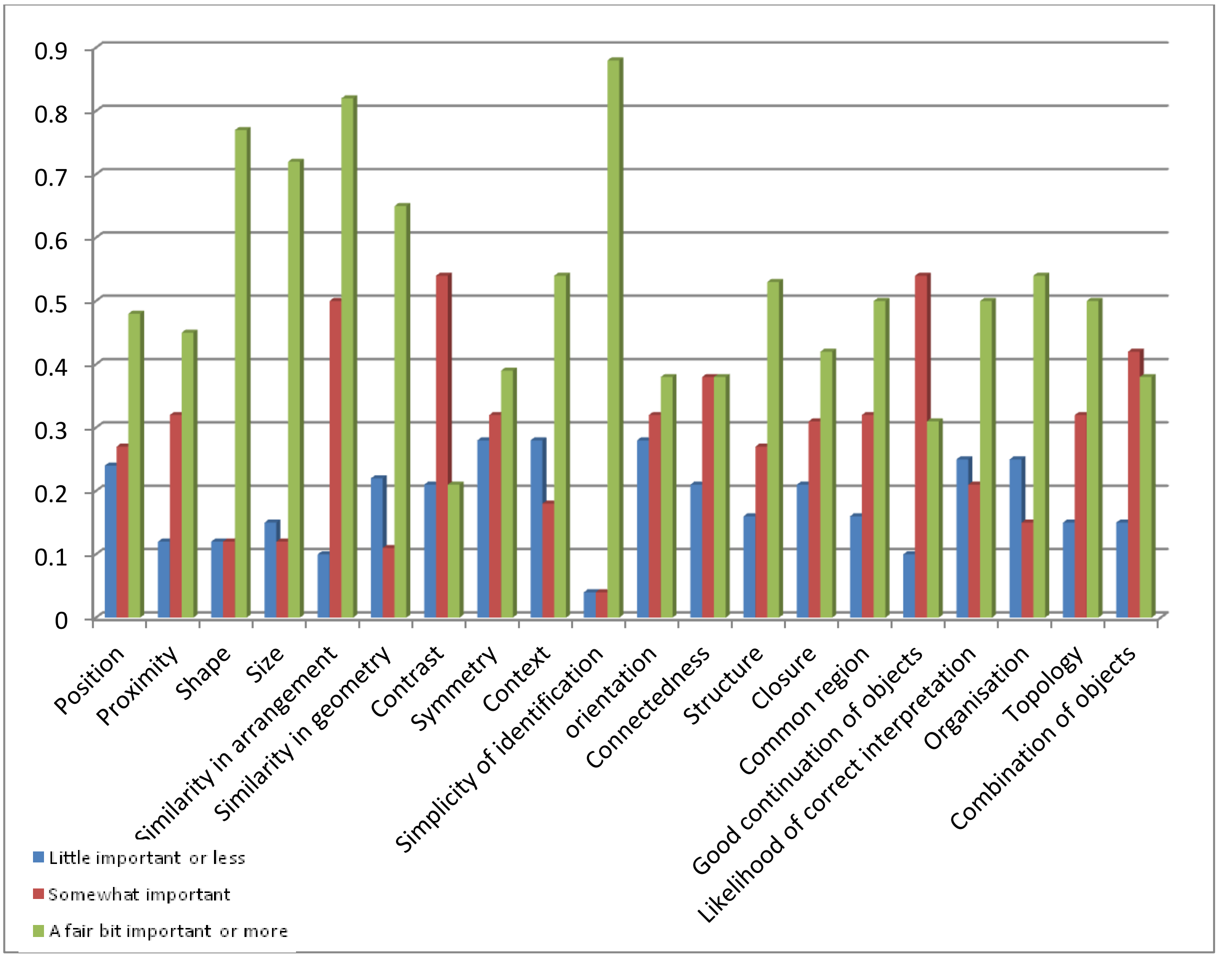



***Figure 4.2 Rated importance of gestalt principles for the interpretation process [283]***

By studying the human understanding of map objects, the excerpt of the hierarchy of topographic map objects has been prepared. Such a hierarchical concept may be learned with a general purpose or the learning system which is closely coupled with the understanding process. Due to this integration of learning and understanding, the knowledge of the ITMUS can be extended. It has been shown in Figure 4.4 b.

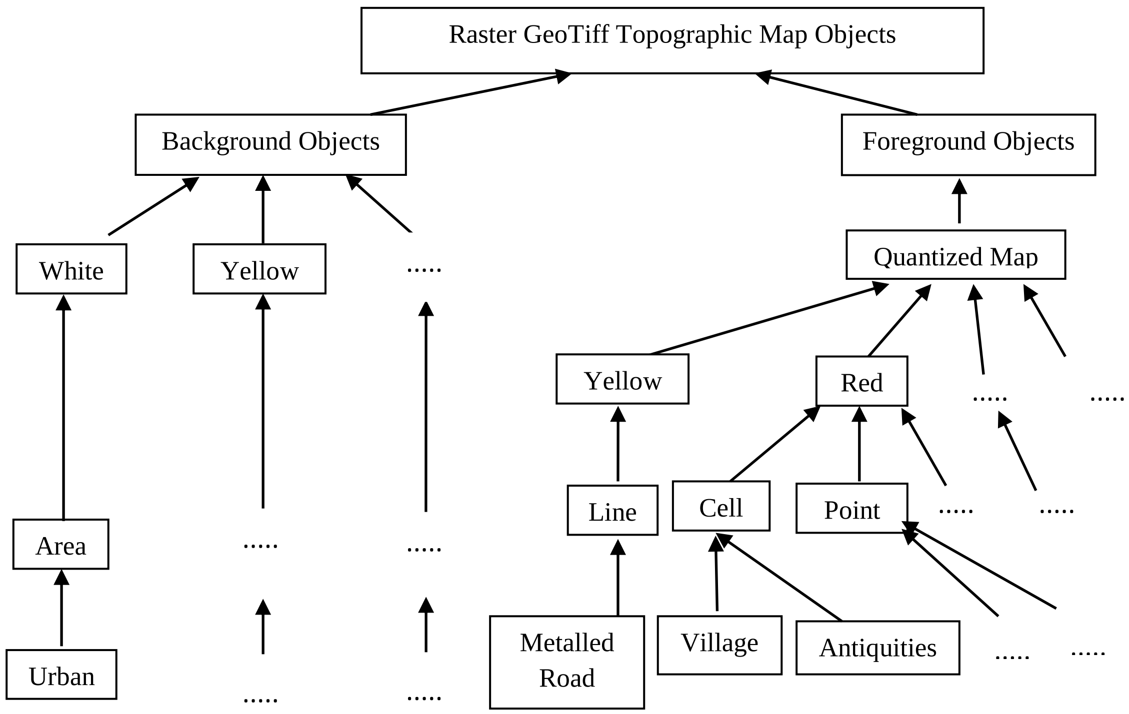



***Figure 4.3 Excerpt of hierarchy of topographic map objects***

As discussed in 3.4.1, the Indian topographic map has numerous complex map objects represented by map objects which convey meaningful information and key to read map has been provided in legend set. Map objects may be heavily interconnected and overlapped by other map objects. This exhibit an interesting challenge for automated recognition and understanding of topographic map. The image processing technique needs to be applied to deal with the complexity of the map. Hence, map pre-processing and segmentation algorithms have been proposed at different levels of image processing operations (as illustrated in Section 3.4.1 using figure 3.3) by correct and adequate object image measurements and rules to recognize patterns.

The map objects can be distinguished based on their geometric attributes like shape, density, structural properties like branch points, etc., and non-geometrical attribute like the color.

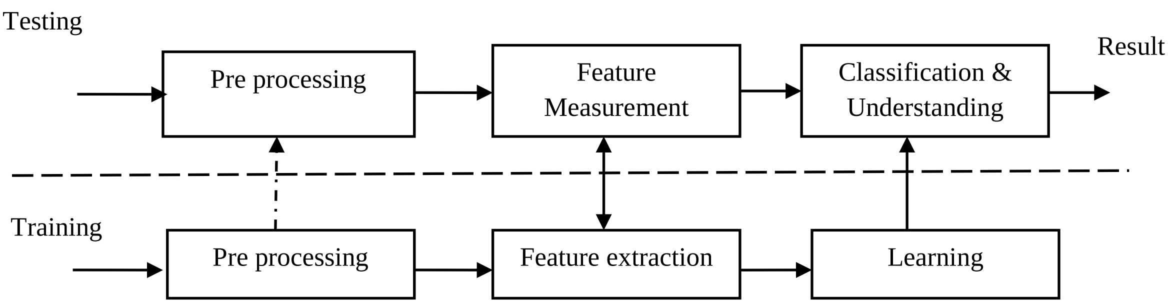



***Figure 4.4a. Basic block diagram of the proposed system [245]***

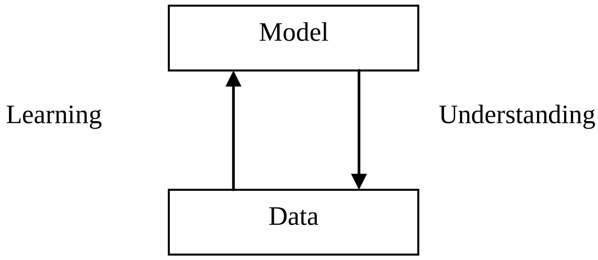



***Figure 4.4 b. Interaction of learning and understanding***

Generally, intentional description or initial knowledge has to be specified or derived in advance and must be hard coded into a system. Hence, the methodological framework has been proposed for LUS module for the extraction of legends from conventional legend set and their numerical representation in terms of shape and structural characteristics. It also describes static rule reduction operations to recognize map legends. It has been proposed to learn the legend's knowledge and interpret the topographic map based on learning. Learning enables the system to adapt new or changing situation. Also, learning reveals the underlying set of rules behind the action. Recall the section 3.4.3 and 3.4.4, which describes an FIS as the first part of ANFIS provides a framework comprising of the if-then rules and reasoning. The ANFIS integrates the rule generation ability of FIS and learning the ability of ANNs [277]. The ANFIS usually perform the mapping between the input and output by learning method to discover optimum parameters of an FIS. Further, adaptive Neuro-fuzzy inference system (ANFIS) [138, 139] has been proposed to achieve a flexible adaptation of the actual legend knowledge and to new or unknown map objects.

The fuzzy rules to define imprecise and highly variable features, the ability to accommodate both data and existing legend's feature knowledge, and ability to generalize the model on unseen map region may find application in emulating human based map understanding and interpretation tasks. Also, during topographic map processing, it becomes necessary to model both low-level, object-specific content (numerical features) as well as high-level content (semantic description), a middle-out approach that combines both top-down and bottom-up approaches seems to be most suitable. Thereby it has been proposed to adopt both, top-down approach from the concepts established from the human knowledge in natural language descriptions towards geographical objects, and bottom-up approach from the objects towards the concepts. Next section has described the proposed system modules in brief.

## 4.4 SYSTEM MODULES DESCRIPTION

The ultimate goal of Indian topographic map understanding system is to be able to understand legend set and objects in map no matter what the circumstances (background, occlusion, etc.) from the topographic map which have been prepared by the Survey of India (SOI). As this task is not trivial to achieve, a human-based approach of legend and map reading seems to be more promising and hence has been adopted. This adopts a step by step approach, starting from segmentation [347] towards complex legend understanding which should be developed. It may consist of a series of operations such as selection of legend set region as an input for the legend understanding subsystem; pre-processing the legend set, color based scheme for legend recognition; connected component labelling and shape analysis of extracting legends; calculation of their geometrical parameters; classification of legends based on the processing of geometrical feature and rule-based pattern matching for their interpretation. The static rules have been adopted which contain geometric parameters as an antecedent and semantic (i.e. meaning) of legend as a conclusion. If antecedents have been evaluated as true, then string describing the semantic meaning of legend has to be returned as an interpretation result. LUS has to store the obtained interpretation result in a legend structure description database.

The human based automated topographic map understanding system has to acquire legend information which has to be used as a key to read a topographic map automatically by a computer program. Hence, the legend understanding module has been proposed. The design of this module consists of an image processing module which basically consists of the pre-processing module, color code assignment and feature extraction and measurement module. Gap filling algorithm has been proposed to reconstruct the gaps/holes due to non-uniform color distribution or color mixing. Morphological binary operations have to be applied to get the structural information of legend region. Color code should be assigned to each legend based on its color and it has to further describe by feature vectors with structural features with their corresponding values. Now, rule-based pattern recognitions has to be employed. The IF-THEN rule, i.e. antesequent, and consequent may be used to create an initial training data set. The intelligent kernel is proposed to adopt rules generated from the initial fuzzy inference system for map understanding. This incorporates the learning of map understanding subsystem. The initial data set has to be modified by replacing semantic meaning/legend description by a unique code which has to be assigned to every Topographic map legends/objects and further provided as the target output for the adaptive system. The flow graph of a proposed system has been shown in Figure 4.5.

The ITMUS is comprising of two main modules such as LUS and MUS. The working of LUS modules have been based on 3 submodules like preprocessing modules, shape analysis and rule based interpretation. The preporocessing module mainly concerned with the task of color code generation which is accomplished by color code generation module. It has been depicted with the help of two dashed lines which is drawn from preprocessing module to code generation module. It's significance is that to show the second module or group of modules is included in the previous module from which dashed lines have been drawn. Similarly in shape analysis module is made up of feature extraction module and shape description module. Hence, two dashed lines have been shown from shape analysis module which have enclosed feature extraction and shape description module.

The MUS module is reusing or calling preprocessing and shape analysis module hence, dashed lines have been drawn from MUS to color code generation, feature extraction and shape description module.

### 4.4.1 Legend Understanding Subsystem (LUS) Module

As stated earlier the research work aimed at simulation of the model in which people studying a topographic map first see the printed legend set on the map. They read legends from legend set and obtain their respective meaning. Afterward, they use that knowledge to recognize map objects that might not be depicted on the map in the same form as found in legend set, but still he succeeds in perceiving it through the formation of their location and shape in nature. Thus the human gaining understanding about the map object by establishing correspondences between structure and their formal description (mind phenomenon) adaptively [195].

It has been proposed to develop a Legend understanding subsystem to make a machine understand the map legends as a representational medium and assign their semantics as well as spatial knowledge encoded therein in the map. The flow graph of the legend understanding sub-modules has been shown in Figure 4.6.

A method for interpretation of topographic map legend sets has been provided in this subsection. The objective in developing this method is to understand the conventional signs of topographic maps. Proposed method first utilizes a prototype search that identifies line or area objects which further characterized by combined properties of geometric attributes. Next, the complete set of geometric attributes is to be iteratively determined. The shape of legend has to be labeled as a string of rule describing legend if they satisfy the conditions of geometric attributes in the IF-THEN rule.

Finally, the pattern searching algorithm determines the characteristic shape of area or line, which should be described by the set of recognized structural features. During interpretation, rules have to compare with obtaining the description. This comparison leads to the determination of legend type. The proposed approach represents a methodological framework for the extraction of legends from a conventional legend set, which would be recognized in terms of shape parameters and structural features. The classification has to be carried out based on shape and structural description specified in static rules.

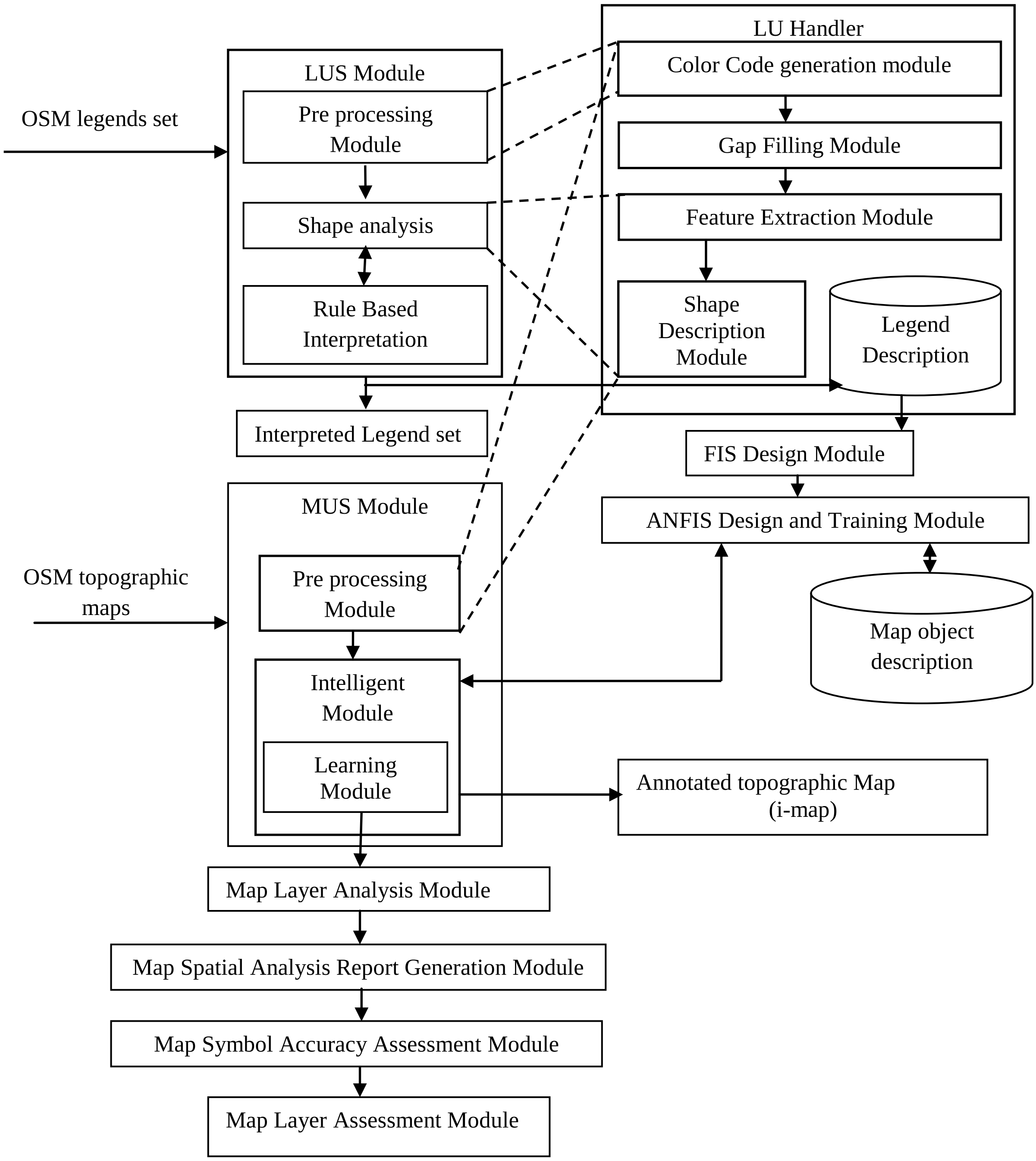



***Figure 4.5 Flow graph of the Proposed System***

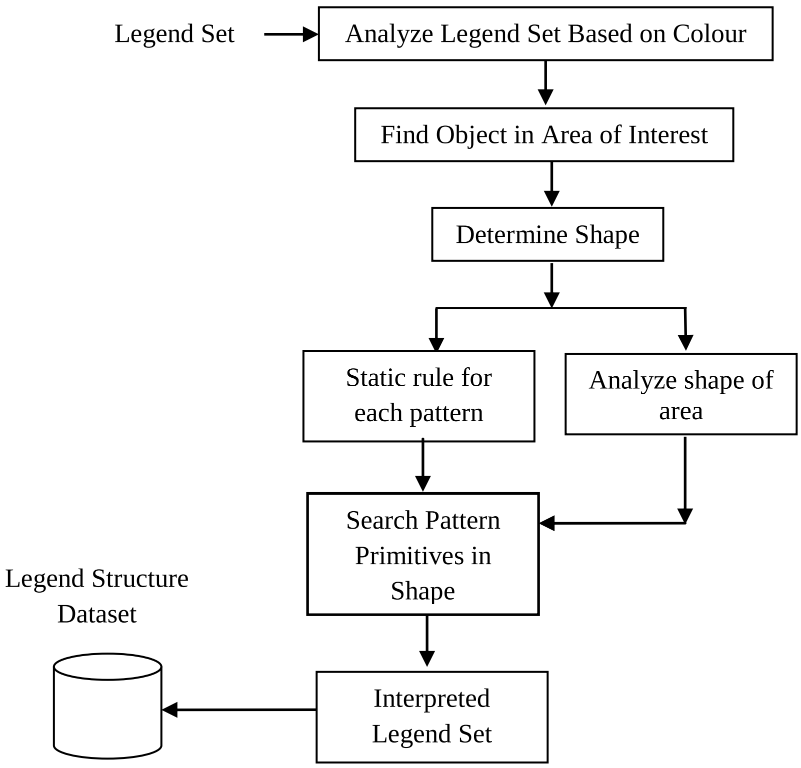



***Figure 4.6 Flow graph of Proposed Legend understanding module***

#### 4.4.1.1 Preprocessing module

In the preprocessing module, the use of average filter has been proposed. This module would perform filtration on the map or map legend using a moving average filter. The operator would affect one pixel of the image at a time, changing its value by an average of pixel values in a 3X3 window centered on that pixel. Filtering would apply iteratively

Next, RGB to Grayscale conversion process is applied to convert the true color map image to the grayscale. This process would eliminate the hue and saturation information. Next, image enhancement would be carried out by gray level slicing (i.e. Intensity level slicing). All the intensities below 240 have to be preserved. For the preservation of other intensities, image enhancement would be done. Hence, morphological operations to remove isolated pixels from an image have been proposed.

#### 4.4.1.2 Color code generation module

This section describes the proposed color code generation module. It has been proposed to segment layers based on combined color code which would be obtained by RGB and gray level thresholding. The proposed color scheme has been referred as ‘Color code book' to emphasize the use of the color code with the feature extraction scheme. Further, for the multicolor legends special scheme is proposed to resolve colors and merge into single color code by considering single structure which possesses representative characteristics of the legend. The number of nonzero elements in image matrix is useful in determining color. Thus, before going for shape analysis, it has been proposed to analyze legends based on their color code.

#### 4.4.1.3 Feature extraction and shape description module

The word "shape" is referring towards the appearance of the object and presenting geometrical information on it. All geometrical information about map objects remains same for all location, scale, and rotational effects. The proposed system needs to contain adequate and useful shape descriptors to represent the map symbols effectively. So it has been proposed to use a set of shape features which are robust, efficient and applicable to map understanding. The statistical feature description containing color feature and 10 invariant geometrical shape descriptors such as branches, end points, Euler number, Solidity, etc. should be desired to be used by the proposed system.As topographic map has been characterized by wide variability and interconnected nature, the proposed statistical shape feature extraction architecture would be based on the labeling of connected components and numerical representation of objects found in the map region. Any feature set may be used with this architecture, but here it would be desirable to use a set of shape features as a geometric shape descriptor. The idea behind the use of those properties would be fairly simple to grasp. The usage of a set of symbol properties as shape features would be most suitable for map object recognition.

Shape representation and description techniques have been classified into two schemes: contour-based scheme and region-based scheme. The classification has been based on the fact that whether shape features are extracted from the contour only or are extracted from the whole shape region. Under each scheme, the several methods are divided into the structural approach and global approach. This category has been based on whether the shape is represented as a whole or represented by segments/sections (primitives). The whole hierarchy of the classification has been shown in Figure 4.7.

In [313], classification and detailed review on shape representation and description techniques have been reviewed. The combination of region based global methods and region-based structural methods have been proposed to shape feature extraction and description techniques. The advantages and limitations of both methods have been discussed in section 3.4.2.

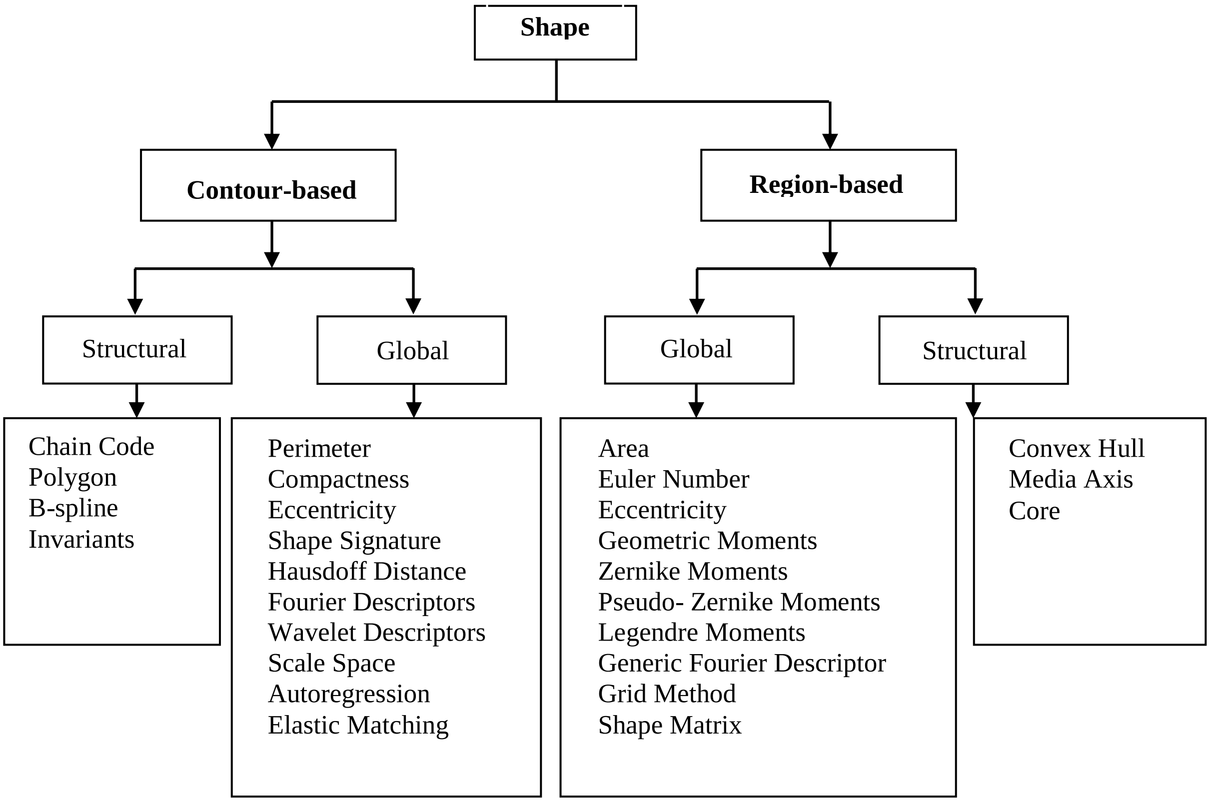



***Figure 4.7 Classification of shape representation and description techniques [342]***

### 4.4.1.4 Rule-based interpretation module

A rule-based classification method has been proposed for the interpretation of topographic map legend sets. Our objective in developing this method has to understand the conventional signs of topographic maps and use this knowledge base as well as rules for subsequent map understanding module.

This module has been proposed to utilize a prototype search that identifies the map object which would be further characterized by combined properties of geometric attributes. Next, the complete set of geometric attributes would be iteratively determined. The shape of legend would be labeled as a string of rule describing prototypes if they satisfy the conditions of geometric attribute association. Finally, the pattern searching algorithm would determine the characteristic shape of area or line, which would be described by the set of recognized structure primitives in the form of rules determining the legend type. Thus the utilization of this legend knowledge would be aimed at preparing initial training data set for map understanding module.

### 4.4.2 Map Understanding Subsystem (MUS) Module

The computer can process large amounts of data and perform the repetitive and tedious task with high precision. A large amount of information is available in topographic maps and it may be used frequently for a variety of operations. But, reading a topographic map without prior knowledge or learning would give a variable and inconsistent interpretation or misinterpretation. Hence, it has been desirable to automate the extraction of information from maps using trained or learned module. Object's shape and structure have been most important features for interpretation as per the gestalt principle [304]. Proposed map understanding subsystem module deals with the development of a system which has been able to understand and interpret topographic map based on prior knowledge, learning and experience. All these properties of human which requires intelligence tend to be employed in machine to understand the topographic map object. One of the characteristics of the topographic map would be its high interconnectedness and overlapping among different map objects. So preprocessing and segmentation of map would be a crucial task. Here, the optimal and the simple solution have been proposed.

The map understanding module has been proposed consisting of five modules: Pre-processing module, Color layer separation module, Gap filling module, Statistical feature extraction and description module, Learning and intelligent module. The Indian Topographic Map would be the inputs for the proposed system. Pre-processing and color layer separation modules would process the map to extract shape feature from it. Before feature extraction, discontinuities, has to be removed and it has been proposed to implement it using digital image processing algorithm. Feature extraction and description enable the system to get an input-output data pair. The learning and intelligent module have been proposed to implement using fuzzy inference system (FIS) which have been proposed by Sugeno [138]. In the FIS, the output of each rule consists of a linear combination of the input shape features added by a parameter. The final output would be a weighted average of each rule’s output giving the number which represents the code assigned for semantic meaning associated with the map object.

#### 4.4.2.1 FIS design module

As described earlier, ANFIS based modeling involves extraction of a set of rules with fixed premise parameters and identification of an optimal fuzzy model.A structure identification and parameter identification are two important modeling aspects. Parameter identification can be performed with ANFIS, however, identification of fuzzy structure from input-output data was proposed by S.L.Chiu in [73]. It has been proposed to the design initial FIS by the design of an initial fuzzy model from the input, output data using a grid partitioning method or subtractive clustering.This initial fuzzy model would be selected based on the fuzzy rules framed by the grid partitioning method [114, 143, 322].The most suitable technique for forming simple legend shape or structure derivation rules is grid partitioning. This technique would be used for framing the rules of the initial fuzzy model. Here the input space would be divided into a fuzzy region to form the antecedents of the fuzzy rules. The Grid partitioned fuzzy space for a two input model, with each input having three membership functions each have been shown in Figure 4.8. The rules obtained grid partitioning method would be then optimized by using ANFIS methodology developed by Jang [48, 138, 141]. This method would optimize the antecedent membership functions by gradient descent algorithm and the consequent parameter by linear least squares estimation.

Thus, initial FIS would generate and extract rules of the legend set structure data which would be used as training data.

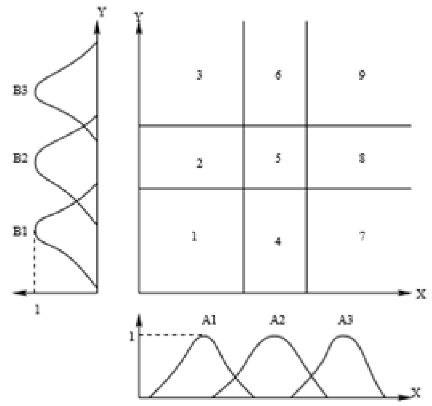



***Figure 4.8 Grid partitioned fuzzy subspace for ANFIS [143]***

The consequent parameters of the initial fuzzy model would be updated by using the Least squares estimation (LSE) algorithm. Similarly, the rules which would be obtained from the grid partition based method would be updated by the neural network, which uses back propagation learning method with the gradient descent algorithm. Updating this would lead to the optimization of the premise parameters of the fuzzy membership functions (Figure 4.8) to give the Initial fuzzy model. The steps that may be followed to in proposed initial fuzzy model are depicted in Figure 4.9.

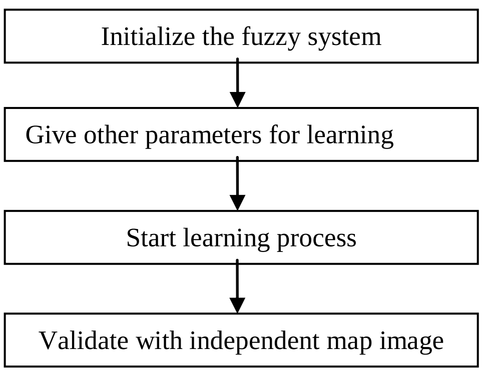



***Figure 4.9 Initialization to optimization steps in the proposed initial fuzzy model***

#### 4.4.2.2 Preprocessing module

In the pre-processing module, the average filter has been proposed. This would replace each pixel value by the average of its neighbors, i.e. the value such that 50% of the values in the neighborhood are above, and 50% are below. The RGB to Grayscale conversion has been proposed that convert the RGB map image to the grayscale intensity image form by eliminating the hue and saturation information while retaining the luminance.

It has been proposed to perform image enhancement by gray level slicing i.e. Intensity level slicing. All intensities below 240 would be preserved. While preserving other intensities image enhancement has to be done by removing isolated pixels ('Clean') from the pattern image by the morphological operation. Filtering has to apply iterative until image no longer changes.

The connected component analysis would be applied to find the number of objects in each image region. Morphological binary operations would be applied for getting the structural information of object region. Thus the number of branch points and a number of end points would be calculated. Using convex hull and minimum bounding parallelogram technique, eccentricity, centroid, solidity and area of object region would be measured. Further, the orientation of the object along y and x-axis would be measured by a minimum bounding parallelogram. Next, object region properties such as extrema, Euler's number, major axis, the minor axis has to be measured as they have the capability to describe the peculiarity of the object. Based on the value of extreme points, the tentative shape of the object would be determined. For example, if extreme points of the temple would give pentagon shape; extreme points of the lighthouse would produce hexagon shape; for extremes of the lightship, pentagon shape would be identified. All structural and geometrical properties calculated for objects and object region have to be stored in vector form with associated binding with the object.

#### 4.4.2.3 Color layer separation module

This section describes the proposed color layer separation module. The essence of the scheme would be a separation of the foreground layers and background layers in a given map region. There is two steps: (i) segmentation into the foreground/background layers; (ii) segmentation of the foreground layers using combined key assigned by RGB and gray level thresholding. Figure 4.5 gives a proposed value for layer separation. The proposed color scheme has been referred as ‘Color code book', however, this color estimation is different from color scheme that would be implemented in LUS.

The color code estimation has been proposed to separate color layers in the topographic map. In current research work, GeoTiff raster topographic maps have to be used in which all colors are standardized and do not include false colors. The foreground color key would be characterized by a vector in RGB space and background color key would be specified by gray index thresholding. In Indian topographic maps, three major background color keys (white, green, and yellow) and twelve foreground color keys (black, blue variants (blue1 to blue3), green, red variants (red1 to red5), black are exists. The proposed color code book algorithm has to be intended to sample pixel values without making a parametric assumption. Mixed pixels between foreground and background have to be handled by a special scheme based on the binary mask. Background colors would be recognized based on a gray index into Green, Yellow, and White. Foreground Layers would be separated into six layers viz. black, brown Yellow, Green, Blue, and Red. Based on RGB pixel thresholding. Out of six foreground color layers, Red color and a blue color layer having a variation which needs further RGB thresholding interval, in individual layers. Thus, 12 foreground layers and 3 background layers would be obtained.

#### 4.4.2.4 Gap filling module

The color layer separation module would result in separate layers with gaps and holes in each layer. In legend set image, the gap is often occurring due to two reasons: the presence of multicolor objects and mixing of pixels at the object boundary. From the extracted layer, any pixel would be considered. It may have three basic properties: type, position, and direction. The type can either of end points or continuous lines. The ending pixel would have exactly one neighbor pixel that belongs to a defined mask. In contrast, a continuous line of pixels has exactly three neighbor pixels or more. Based on this assumption, it has been proposed to apply the 3x3 mask for detecting endpoints. Once an endpoint has been detected, several other criteria like the angle, distance and orientation would be taken into consideration for reconnecting broken lines or filling holes. Initially, in the proposed approach, the emphasis has to place on nearest endpoint detected with appropriate angle and orientation. Once, the nearest endpoint is detected, then control points should take from two endpoints and the two points which may backtrace from pixel commencement from the corresponding endpoint to fill up the gap. It has been depicted in Figure 4.10.

#### 4.4.2.5 Feature extraction and shape description module

The shape and structural features would be efficient to describe map objects. Once segmentation and reconstruction would be applied to the map, the map objects in each layer have to be described and represented in the computer for further processing. Some of the work has been done in an automated process for extracting object boundaries from color images through color image segmentation and skeletonization.

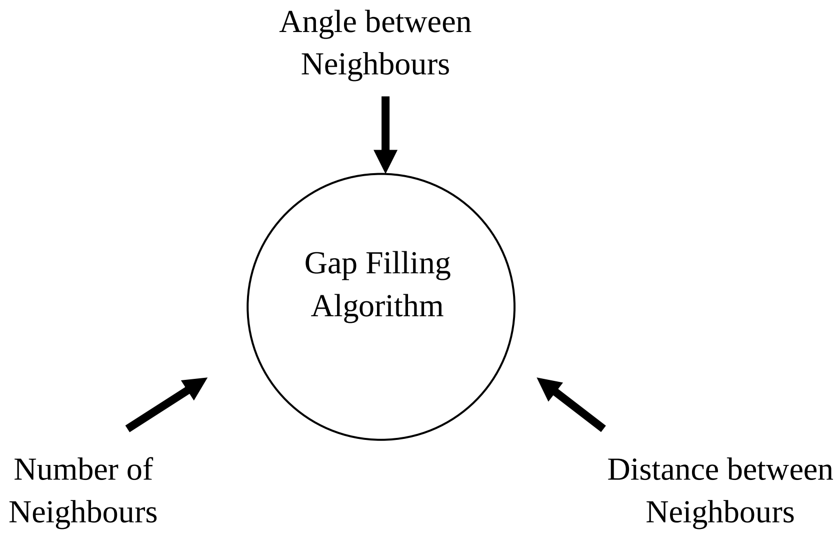



***Figure 4.10 Proposed gap filling algorithm***

The segmentation of a color image has been performed to get an object or all the objects, after which they have sampled its boundary and the generated points have been used to construct the Delaunay triangulation. Then they have measured ‘Voronoi’ vertices for all faces of the triangulation as a feature descriptor. Many different representation schemes such as chain codes, Polygonal Approximation, Signatures, Convolution hull, Boundary Segments, the skeleton of a region boundary does exist [342]. Object descriptors may be length or curvature, topological descriptors such as no. of connected elements and texture primitives (mean or standard deviation measures), shape descriptors such as eccentricity, solidity etc. would be effective. Also, morphology may be used in a mathematical context as a tool to extract map object components. Morphology may provide boundaries, skeletons, or the convex hull. However, boundary based descriptor or representation would not be helpful in the case of the topographic map object. A segmented map object may contain multiple boundaries. Also, small occlusion or distortion present in object boundary would result in large difference and variance in descriptors/disruption. However, shape features are less sensitive to noise and distortions. Hence, it has been proposed to use shape features to obtain a map object's description.Every map object would be detected in each individual layer would be undergone image processing and morphological operations to measure shape features. Mostly cell type map object would have been easily discriminated by their color and represented by their closed boundaries and, connected pixels. Each map object exhibiting cell, a linear or dot object would be measured for shape properties using various mathematical operations. The shape and structure parameter values would be derived described to obtain the feature descriptor. Some shape parameters will be derived from an object's connected component and their properties will be encoded in a map object feature descriptor. These shape descriptors will be given to adaptive Neuro-fuzzy model to train it as well as to evaluate it for determining semantic meaning of map objects.

### 4.4.2.6 ANFIS design and training module

The Fuzzy inference system would provide a computing framework which is based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. The selection of the FIS would be the major concern in the design of an ANFIS. The first-order Sugeno fuzzy model has been proposed to use to generate fuzzy rules from a set of input-output data pairs generated in a rule-based classification module. Input here would be the legend's feature description and output will be the semantic meaning of the legend which is encoded in number. These input-output data pairs would be converted into a training data matrix. Among many FIS models, the five layer Sugeno fuzzy inference model has been proposed to generate ANFIS output structure.

ANFIS model design has been proposed for map understanding consisting of two sections: learning and training. In the learning section, the selection of the number and type of membership function is an important aspect. The building of the ANFIS model would require the partitioning of the input - output data into rules. This can be achieved by using a number of methods such as grid partitioning, subtractive clustering method and fuzzy c-means (FCM) [114].As the number of input feature vectors is less, the grid partitioning would be more efficient. The prior legend's feature dataset would be less in size. Hence, Grid partitioning has been proposed to generate initial FIS from legend's feature description (initial training data). However, as considered to the time complexity, subtractive clustering, and fuzzy c-means techniques have been proposed to model multiple independent ANFIS structures to incorporate them in MUS kernel.

The subtractive clustering method has been proposed to optimize the initial fuzzy model. The subtracting clustering technique locates the cluster centers in the input-output data pairs. It helps to determine the rules which are scattered in input-output space. Here, each cluster center gives an indication of the presence of a rule. The subtractive clustering determines the premise parameters. This would be important as an initial value, which is close to the target value, will result in the quick convergence of the model towards its target during the training. The subtractive clustering method uses, potential which is defined as,

$$P_1(z_i) = \sum_{j=1}^{N} e^{-\alpha\|z_i - z_j\|^2} \qquad \text{Eq. (4.1)}$$

where, $P_1(z_i)$ denotes the potential of the data point/sample$(z_i)$. The data point/sample of its neighborhood data points/samples will have high potential value, however, remote or isolated data point/sample will possess a low value of potential.The potentials have been a monotonic function which calculates Euclidian distances $\|z_i - z_j\|^2$from all the other data points. The datapoints having a potential above a certain preset value (say 0.5) would be considered as cluster centers. Once the cluster centers determined, the initial fuzzy model would be eventually extracted. The method to determine the number of rules and initial rule parameters has been briefly described in [73].

The FCM has been proposed to model some ANFIS models for classification of particular topographic map object's category. The FCMhas to be used in ANFIS model which is being designed to interpret the topographic map objects which are less complex and whose shape feature description holds sufficient discriminating power to classify those objects which exhibit less resemblance with other map objects. FCM partitions a collection of n vectors into $x_i$, where, i=1,2,...,n fuzzy groups, and would determine a cluster center for each group such that the objective function of dissimilarity between expected and measured output should be reduced. In order to obtain a less number of fuzzy rules, FCM clustering has to be applied for this task. The FCM clustering technique would systematically create the fuzzy MFs and a fuzzy rule base for ANFIS. During training, input-output data pair would be generated to train an ANFIS model. The data pairs would consist of the ANFIS model inputs and the corresponding output. The membership function parameters would change during the learning process. The adjustment of membership function parameters would be served by a supervised learning of the input-output data pairs. A hybrid learning method integrating the least squares and the gradient descent algorithm has been proposed.

#### 4.4.2.7 Intelligent module

The aim of building intelligent module is to model many ANFIS structures, adopt learning mechanism to train and evaluate them.The 5-layer ANFIS structure has been proposed to use in the implementation of the intelligent module. For premise parameters, the output is a linear combination of consequent parameters. The two pass hybrid learning algorithm has been proposed in which consequent parameters would be obtained by least square error estimation and premise parameters would be modified using a derivative of squared error [143]. From the modeling viewpoint, incorporation of robust shape feature variables as an input training data result in a practical model has been proposed for map object semantic understanding problem. In the proposed module, selection and integration of ANFIS model would be accomplished by considering the least modeling error.

#### 4.4.2.7.1 Learning module

The Adaptive network based fuzzy inference system (ANFIS) [73, 141, 143] is a hybrid system comprising of the neural network and the fuzzy logic. The proposed system has been data driven consisting of two steps. Here, at first a formation of a fuzzy inference system has been proposed. The FIS has been characterized by the extraction of the fuzzy rules of the input-output data set. In the second step, the neural network has to be employed to fine tune the rules of the initial FIS model.The neural network would be trained using ANFIS methodology. This work would be an endeavor to use the ANFIS as an understanding technique for accomplishing the training of the network faithfully with plenty of topographic map data. Each ANFIS possesses the network, corresponding to a m-rule FIS, which has been made of 5 layers. The two inputs and one output ANFIS architecture has been illustrated. The specification of each layer has been given below.

Layer 1: The node function at each node in the first layer has been given as,

$O_i^1 = \mu_{A_i}(x), \qquad i = 1, 2$

$O_i^1 = \mu_{B_{i-2}}(y), \quad i = 3, 4$ Eq. (4.2)

where $\mu_{A_i}(x)$,and $\mu_{B_{i-2}}(y)$ can adopt any fuzzy membership function (MF). In this research work, the 10 Generalized bell Membership function has been proposed to use.

$Gbell(x; a, b, c) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}}$ Eq. (4.3)

The $\{a_i, b_i, c_i, \sigma_i\}$ are the parameter set that changes the shapes of the Membership function. Parameters in this layer would be referred to as the premise parameters.

Layer 2: The firing strength of each node can be specified via multiplication:

$O_k^2 = \omega_k = \mu_{A_i}(x)\mu_{B_{i-2}}(y)$ Eq. (4.4)

where, $i = 1, 2; j = 1, 2; k = 2(i-1) + j$

Layer 3: The ratio of the $i^{th}$ rule's firing strength to the sum of all rules' firing strength has been calculated at each node. For the $i^{th}$ node, it has been calculated as:

$O_i^3 = \overline{\omega}_i = \frac{\omega_i}{\omega_1+\omega_2+\omega_3+\omega_4}, i = 1, 2, 3, 4$ Eq. (4.5)

where$\omega_i$has been referred to as the normalized firing strengths.

Layer 4: In this layer, each node has the following function:

$\omega_i^4 = \overline{\omega_i} z_i = \overline{\omega}_i(p_i x + q_i y + r_i), i = 1,2,3,4$ Eq. (4.6)

where $\omega_i$ is the output of layer 3, and $\{p_i, q_i r_i\}$ is the parameter set. Parameters in this layer would be referred to as the consequent parameters.

Layer 5: The overall output would be computed in this layer at a single node by the summation of all incoming signals, which would be expressed as:

$$O_1^5 = \sum_{i=1}^{4} \frac{\omega_1 z_1 + \omega_2 z_2 + \omega_3 z_3 + \omega_4 z_4}{\omega_{1+}\omega_2 + \omega_3 + \omega_4} \quad \text{Eq. (4.7)}$$

Thus, the ANFIS has two sets of modifiable or adjustable parameters, namely the premise and consequent parameters. The learning process would modify/tune the premise parameters in the layer 1 and the consequent parameters in the layer 4 until the desired response of the FIS has been obtained. The hybrid learning algorithm [138, 143] has been proposed to train and adapt the FIS. When the premise parameter values of the membership function are fixed, the output of the ANFIS is a linear combination of the consequent and has been given by Eq. 3.9. The Eq. 3.9 has been rewritten as:

$$z = (\overline{\omega}_1 x)p_1 + (\overline{\omega}_1 y)q_1 + (\overline{\omega}_1)r_1 + .. + (\overline{\omega}_4 x)p_4 + (\overline{\omega}_4 y)q_4 + (\overline{\omega}_4)r_4 \quad \text{Eq. (4.8)}$$

But, when the premise parameters are not fixed, then the search space becomes greater resulting in slow convergence. of training becomes slower. Hence, hybrid learning approach has been proposed. The hybrid learning algorithm converges faster by reducing the search space dimension. It has been given in detail in the next subsection.

#### 4.4.2.7.1.1 ANFIS least squares batch algorithm

As discussed previously, the use ANFIS which consists of forward stroke and backpropagation algorithm has been proposed. The ANFIS learning technique calculates and updates the parameter based on the derivative of the overall error. Hence it is named as offline learning or batch learning paradigm. The training procedure has to encompass the following steps:

i. Propagate all shape feature values of map objects and target output (semantic meaning of map object) from the training data and obtain the consequent parameters by applying a least square algorithm iteratively. The antecedent parameters would be constant.

ii. The proposed algorithm would perform the function of a forward pass by using the least square estimator and backward pass by gradient descent algorithm. It first needs to map the object features with the membership functions of inputs and parameters. Then it would map the data of input space to output space with the MFs of output variables and parameters. The parameters finding would result in an adjustment of the shapes of membership functions and alteration through learning. The adjustment of these parameters would be accomplished by a gradient vector. Once this gradient would be determined, the system would adjust these parameters to diminish the error between it and then gives expected output system.

During the training process, the training dataset would be offered to the ANFIS in a recurrent manner. The each cycle through all the training examples represents an epoch. Each epoch consists of a forward pass and a backward pass. Additionally, the process of obtaining a gradient vector which consists of derivative of error measure with respect to each parameter is important and illustrated below. Considering the output function of node $i$ in layer $l$.

$$x_{l,i} = f_{l,i}(x_{l-1,1}, \dots, x_{l-1,N(l-1)}, \alpha, \beta, \gamma, \dots) \qquad \text{Eq. (4.9)}$$

where, $\alpha, \beta, \gamma, ..$ are the parameters of $i^{th}$ node.

The sum of the squared error defined for $P$ entries, has been defined as:

$$E_p = \sum_{k-1}^{N(L)} (d_k - x_{l,k})^2 \qquad \text{Eq. (4.10)}$$

Where $d_k$ is the desired output vector and $x_{l,k}$ both for the $k^{th}$ of the$p^{th}$ desired output vector. The gradient vector would be calculated to pass derivative information starting from the output layer and going backward layer by layer to the input layer has to be reached. If α is a parameter of the $i^{th}$ node at layer $l$.Thus, it would obtain the derivative of the overall error measure E with respect to α as shown below.

$$\frac{\partial E}{\partial \alpha} = \sum \frac{\partial E}{\partial \alpha} \qquad \text{Eq. (4.11)}$$

Thus the generic parameter α would become:

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha} \qquad \text{Eq. (4.10)}$$

where, $\eta$ is the rate of learning. So, parameter$\alpha$is defined as

$$\alpha_{new} = \alpha_{old} - \frac{(-\eta)\partial E}{\partial \alpha} \qquad \text{Eq. (4.11)}$$

Then Eq. (4.10) would be used to find out the derivative of the error measures. The gradient vector would be found for each training data entry, whose input parameters would be updated at the end of a backward pass by using Eq. 4.10 [141, 143].

### 4.4.2.8 Map layer analysis module

For a layer based understanding of topographic maps, a separate module has been proposed as a map layer analysis module.The preprocessing module and color layer separation module would facilitate the layer based analysis. The intelligent module has been proposed in the previous section has used to interpret the symbols. The aggregation of map objects understanding created by different ANFIS model would be integrated internally and semantic meaning which would obtain in ANFIS evaluation will be added in intermediate categories. For example, cart track metalled road would be added in Communication category and also be recognized in a thematic layer named as communication. The statistical analysis of thematic layers would also be recorded in the data structure. Also, map layer comparison of system generated layer and manual delineation with respect to success and failure in layer extraction would be demonstrated. It has been proposed to carry out this comparison in the form of the intersection of a system generated layer and mask of the manually delineated layer.

#### 4.4.2.9 Map spatial analysis report generation module

The interpretation and resulting understanding of topographic map would consist of classification result along with spatial, topographic and structural details. The classification result would be consisting of symbol's semantic meaning derived from other modules. Spatial details such as latitude and longitude, topographic details such as the general shape of a symbol, structural details such as shape feature measured by other module need to be recorded and maintained. For the map spatial analysis, report generation module has been proposed to have a map object description in a separate file which may be ready to use in any other geoinformation based system or applications. Also, proposed module would generate a text file containing summarization of map understanding with derived map object's semantic meaning, and their geolocation. This information would be required for the accuracy assessment module.

#### 4.4.2.10 Map symbol accuracy assessment module

The map symbol accuracy assessment module design incorporates comparison between system generated map understanding summary with their local coordinates and standard metafile generated by Survey of India in Microstation software.This module maintains a table, keeping track of recognized symbols, their location and number of instances occurred in training map data as well as checking map data. The accuracy assessment table would perform a job of providing an assessment of the accuracy of ITMUS based on correctly interpreted symbols.

#### 4.4.2.11 Map layer assessment module

For the assessment of the map layer extraction, a separate module would be provided to form a framework to load the system generated color layers of the topographic map, then the manually delineated layer in the same area and converted into a binary mask. Further, this module would implement overlaying operation between the system and manual result and apply layer extraction measures for showing the correctly extracted map layers.

### 4.5 SYSTEM REQUIREMENTS

Computer systems for Topographic map data acquisition, archiving, and processing, represents the future of computer assisted understanding and reverse and generalized cartography [318]. The computer system has been considered as the workstation between a GeoTIFF topographic map archival and the referring client. Therefore, the acceptance of the system is highly dependent on machine configuration and performance. Experience in evaluating commercial machine for map understanding describes hardware and software requirements for smooth operations on a map like preprocessing and actual understanding that could be used for making interpreted map available to the end user. This machine/computer must be able to handle the large size of map images to be viewed efficiently. The proposed system would provide geoinformation based output, which may allow the proposed systems to grow as map understanding and information extraction technology which evolve cyclically with varying size of the area of interest. The software requirement for the proposed system is MATLAB version 2013 and higher version. Hardware requirement is i7 processor with a minimum speed of 2.60GHz, and 8.00 GB installed RAM on 64 -bit operating system. This is a minimum requirement for the proposed system to understand part of the topographic map of size 512 by 512 pixels with good visibility of interpretation result.

## 4.6 INDIAN TOPOGRAPHIC MAP DATA

Topographical maps, also known as general purpose maps, are drawn at relatively large scales. These maps show important natural and cultural objects such as relief, vegetation, water bodies, cultivated land, settlements, and transportation networks, etc. These maps are prepared and published by the National Mapping Organisation of each country. For example, the Survey of India prepares the topographical maps in India for the entire country; USGS is preparing topographic map for US. The topographical maps are drawn in the form of series of maps at different scales. Hence, in the given series, all maps employ the same reference point, scale, projection, conventional signs, symbols and colours. The topographical maps in India are prepared in two series, i.e. India and Adjacent Countries Series and The International Map Series of the World both in analog and digital form.

India and Adjacent Countries Series: The preparation of maps for the adjoining countries was abandoned and the Survey of India confined itself to prepare and publish the topographical maps for India as per the specifications laid down for the International Map Series of the World. The existing digital data on Polyconic /Everest projection is converted to UTM WGS84 and then OSM data is generated. For updation, the updated OSM data of all 16 component sheets of 1:50,000 scale are used. Since the data is received from concerned state GDCs, therefore the accuracy mainly depends on existing 1:250,000 scale data and the OSM data of component sheets supplied by state GDCs.

For example, the digital data of sheet No.53C in Polyconic /Everest datum is first converted to OSM digital data in UTM/WGS84 datum. All the standard procedure e.g. clipping, merging from adjoining sheets, were followed for the conversion. The symbology as applicable for 1:50,000 OSM sheets was adopted for 1:250,000 scale OSM sheet. The converted sheet in OSM is named as H43Q. The details of topographic OSM series which are used in this study has been given in Table 4.1.

***Table 4.1 Indian Topographic Map data details***

| Sr. No. | Data Sheet Number | | Territory Name | Scale | Year of Updation |
|---|---|---|---|---|---|
| | Sheet No. (Polyconic) | Sheet No. (OSM) | | | |
| 1 | 53C/7 | H43Q7 | Jind Haryana | 1:50000 | 2007 |
| 2 | 53F/6 | H43L6 | Sirmaur Himachal Pradesh | 1:50000 | 2011 |
| 3 | 53F/7 | H43L7 | Yamunanagar, Haryana | 1:50000 | 2009 |
| 4 | 53F/11 | H43L11 | Boundary area of Sirmaur, H.P., Dehradun, U.K., Saharanpur, U.P., Yamunanagar, Haryana | 1:50000 | 2009 |
| 5 | 53K/1 | H44M1 | Haridwar, Uttarakhand | 1:50000 | 2011 |

A DRG as TIFF is a georeferenced raster image of a published map saved in GeoTIFF format. Files distributed in this format are scanned images of Survey of India topographic maps. DRGs are georeferenced to the plane ground coordinates of the Universal Transverse Mercator (UTM) coordinate system. The DRG product contains georeferencing information in three places for convenience of end users with different software tools: in the TIFF file following the GeoTIFF standard (version 1); in a separate metadata file; and in an optional world file (*.tfw) which contains partial georeferencing information. The SOI DRG product consists of two mandatory physical files: the TIFF image and a text file of metadata. A third file, an Arc/Info world file, has been included, though this is not required by the product standard. The associated DRG image (.TIF), world (.TFW), and metadata (.FGD) files incorporate an intelligent data set name (DSN) consisting of descriptive metadata wrapped around a standardized kernel that describes the spatial location of the file. SOI DRG images are stored in TIFF version 6.0, using PackBits compression (run-length encoding).

DRG's can be easily combined with other digital cartographic products such as digital elevation models (DEM) and digital orthophoto quadrangles (DOQ). DRG's are made by scanning published paper maps on high-resolution scanners. The raster image is georeferenced and fit to the Universal Transverse Mercator (UTM) projection. Colors in GeoTIFF DRG are standardized to remove scanner limitations and artifacts. The GeoTIFF version of this product is exactly the same image as the native format which includes conventional signs (legend sets). GeoTIFF is a public domain metadata standard which allows georeferencing information to be embedded within a TIFF file. The potential additional information includes map projection, coordinate systems, ellipsoids, datums, and everything else necessary to establish the exact spatial reference for the file. The proposed system has ability to interpret geocoding metadata contained within GeoTIFF products through the implementation of image processing package - Map geo converter. The legend set present on GeoTIFF map has been given below. Some topographic map sample regions selected form 53C7, 53F6, 53F7, 53F11 and 5K1 have been shown in Figure 4.12 from Figure 4.12 (a) to Figure 4.12 (e).

The study of topographical maps is simple. It requires the reader to get acquainted with the legend, conventional sign and the colours shown on the sheets. The conventional sign and symbols depicted on the topographical sheets are shown in Figure 4.11. The conventional signs defined by mapping agencies of each respective country is different however, the basic concept behind using it is same. For example, water objects or water bodies are defined by legends in blue color but color tone and structure of legend may be different. Interpreting the colored lines, areas, and other symbols is the first step in using topographic maps. Objects are shown as points, lines, or areas, depending on their size and extent. For example, individual houses may be shown as small pink squares however, in US topo it is shown by black square. For larger buildings, the actual shapes are mapped. In densely built-up areas, most individual buildings are omitted and an area tint is shown. On some maps, post offices, churches, city halls, and other landmark buildings are shown within the tinted area. In Figure 4.12 a, these types of objects can be identified.

The first map objects usually noticed on a topographic map are the area objects, such as vegetation (green), water (blue), and densely built-up areas (white). USGS have defined densely built up area in gray or red. Many objects are shown by lines that may be straight, curved, solid, dashed, dotted, or in any combination. The colors of the lines usually indicate similar classes of information: topographic contours (brown); lakes, streams, irrigation ditches, and other hydrographic objects (blue); land grids and important roads (red); and other roads and trails, railroads, boundaries, and other cultural objects (black). The Survey of India is using purple color for showing District boundary, however, USGS is using same color as a revision color to show all object changes. Various point symbols are used to depict objects such as buildings, campgrounds, springs, water tanks, mines, survey control points, and wells. Names of places and objects are shown in a color corresponding to the type of map object. It has been observed in Figure 4.12. Many map objects are also identified by labels, such as “Gurudwara” which are generally provided in conventional signs as a adminstrative, locality ot tribal names

Topographic contours are shown in brown by lines of different widths. Each contour is a line of equal elevation; therefore, contours never cross. They show the general shape of the terrain. To help the user determine elevations, index contours are wider. Elevation values are printed in several places along these lines. Figure 4.12 b shows the mountaneous or hilly sample region.

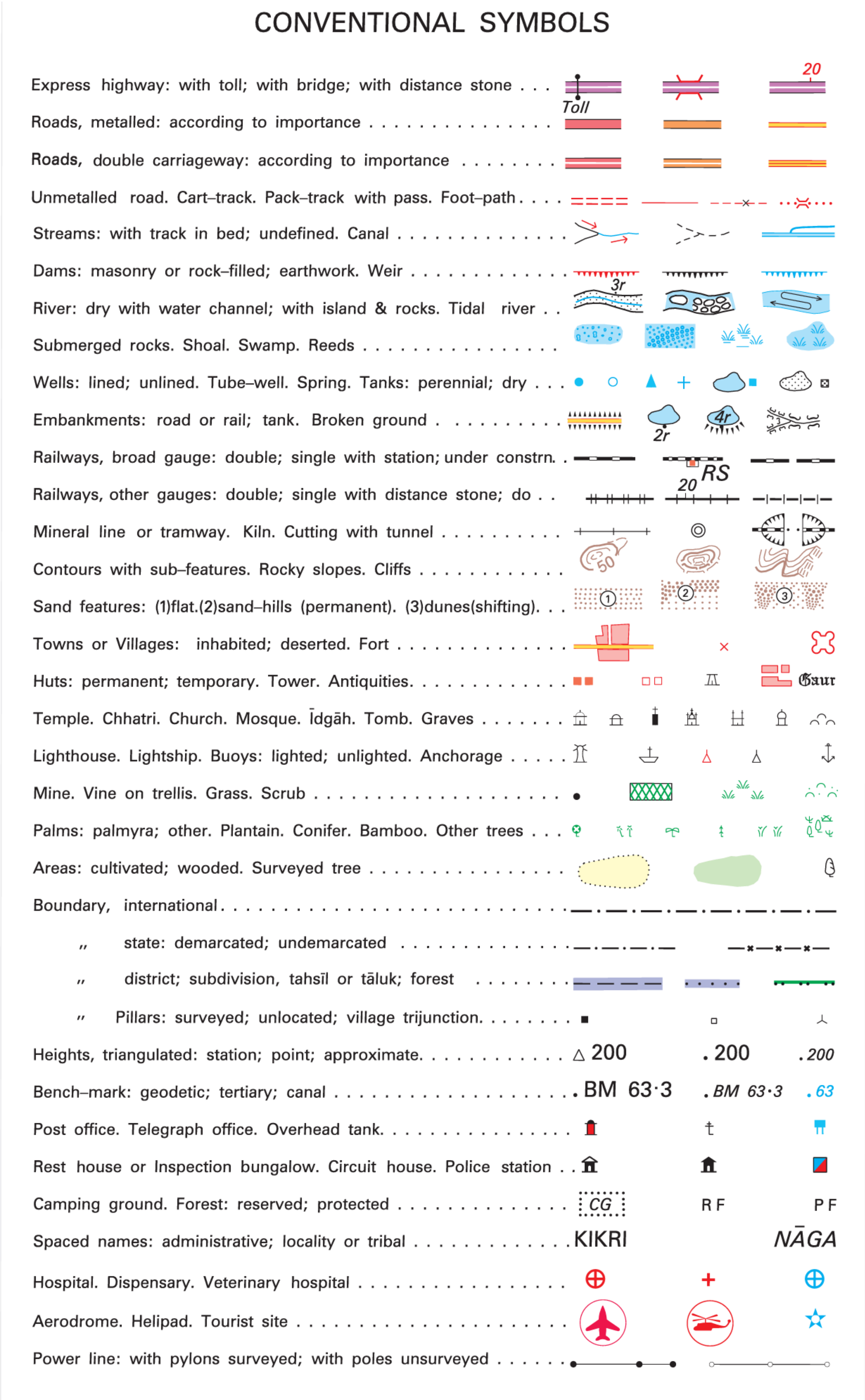



*Figure 4.11 Conventional signs developed by Survey of India, Dehradun.*

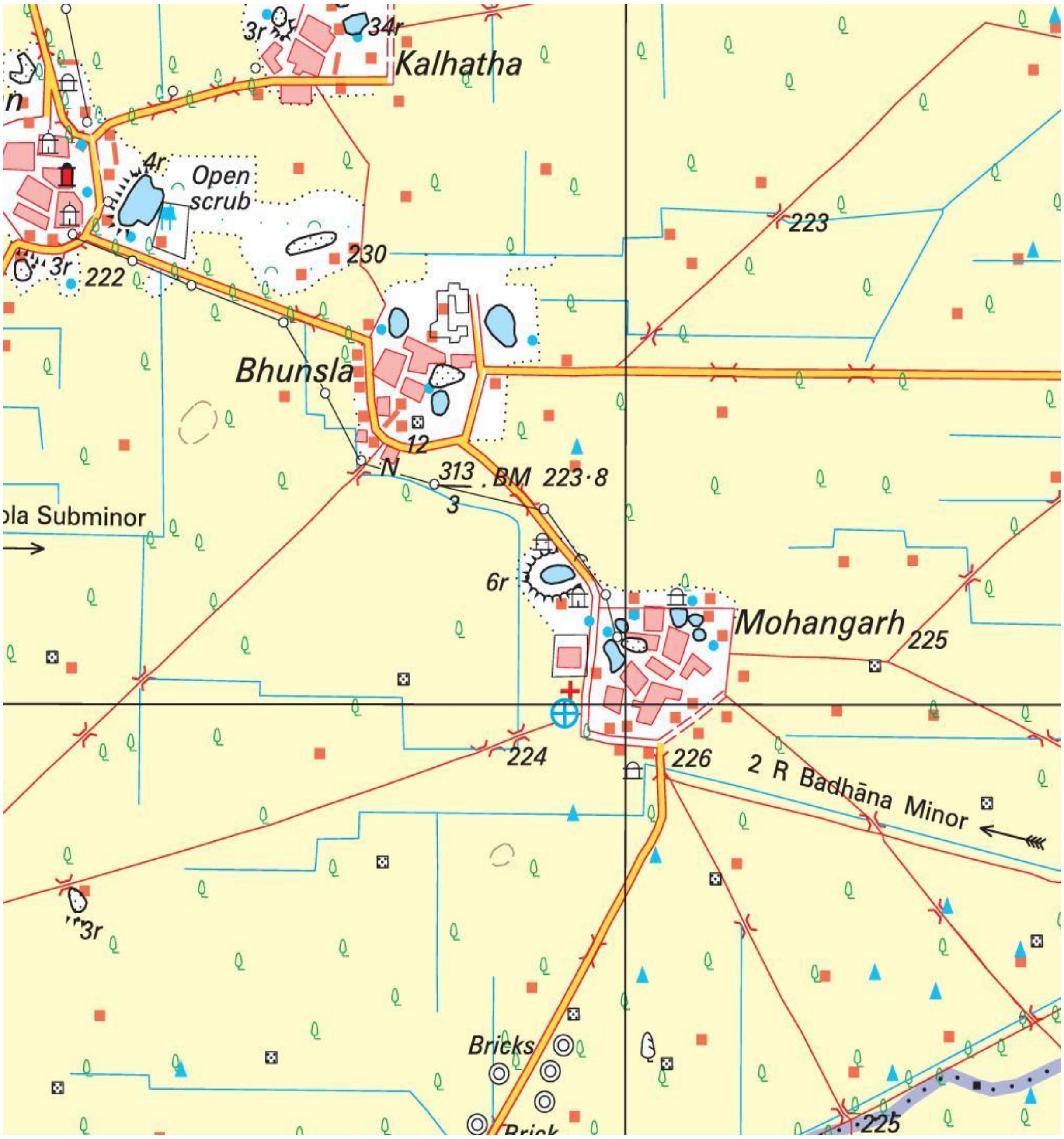



*Figure 4.12(a) Sample regions of Indian Topographic OSM 53C7-Region 1*

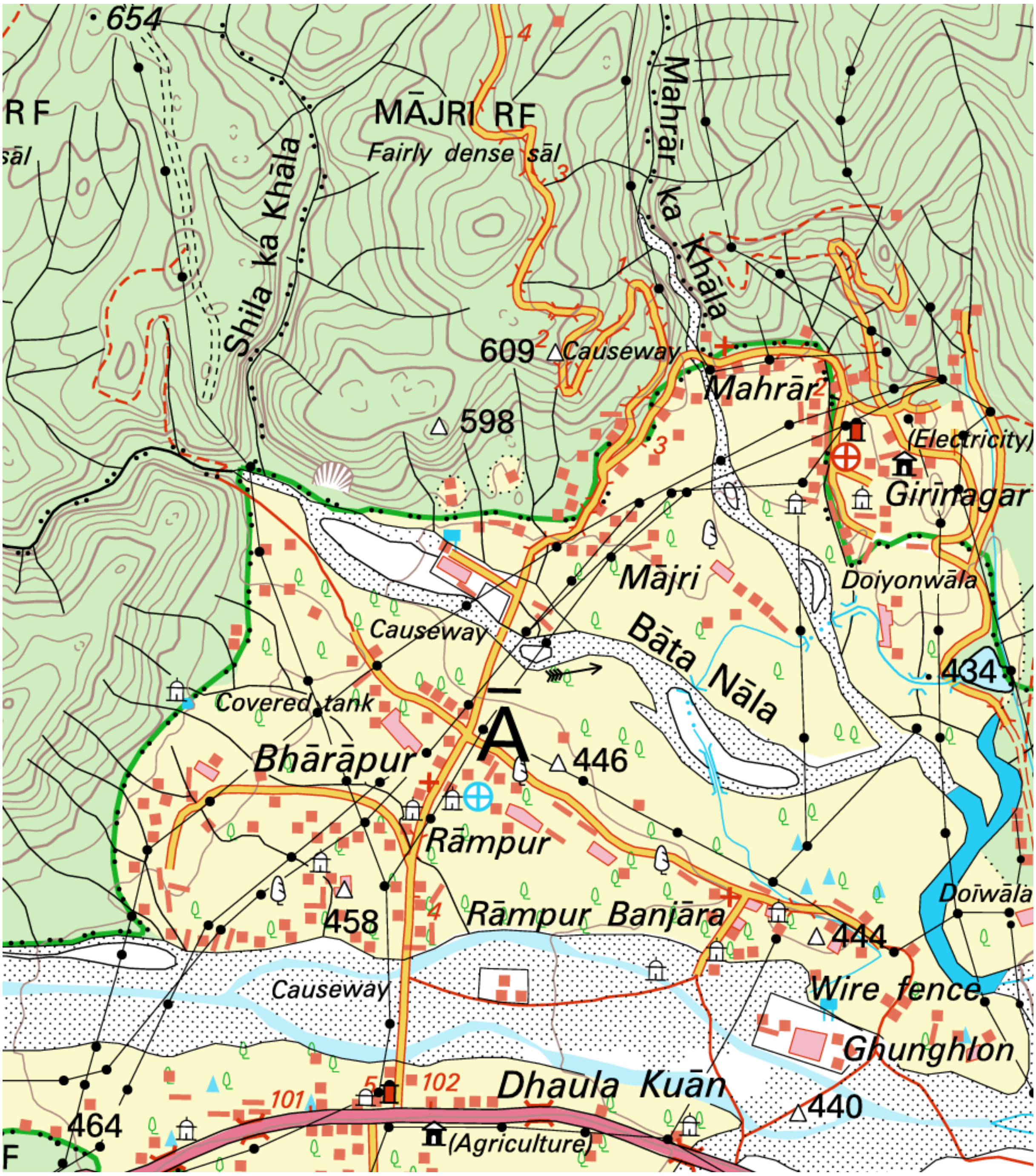



*Figure 4.12 (b) Sample regions of Indian Topographic OSM 53F6-Region 1*

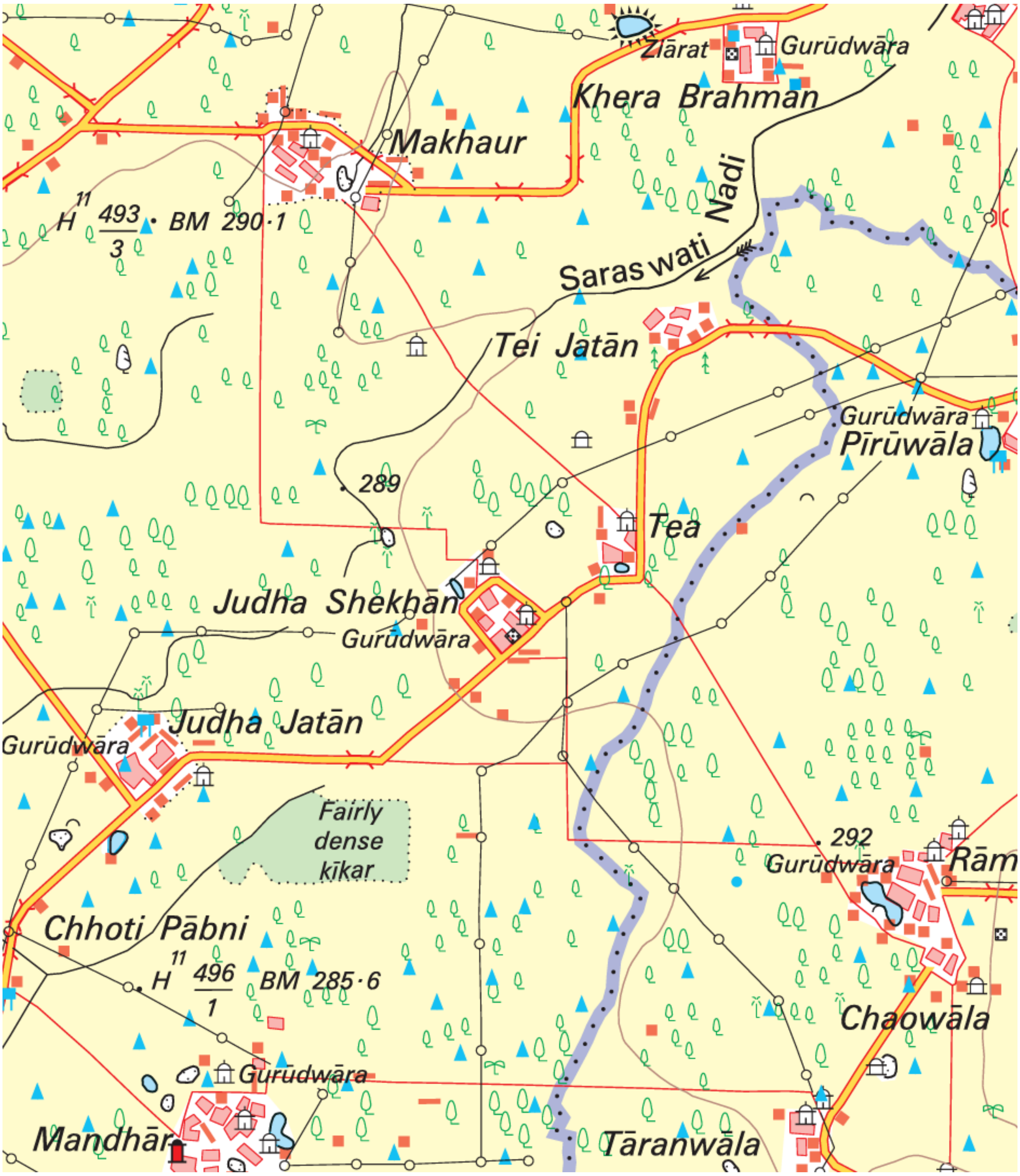



*Figure 4.12 (c) Sample regions of Indian Topographic OSM 53F7-Region 1*

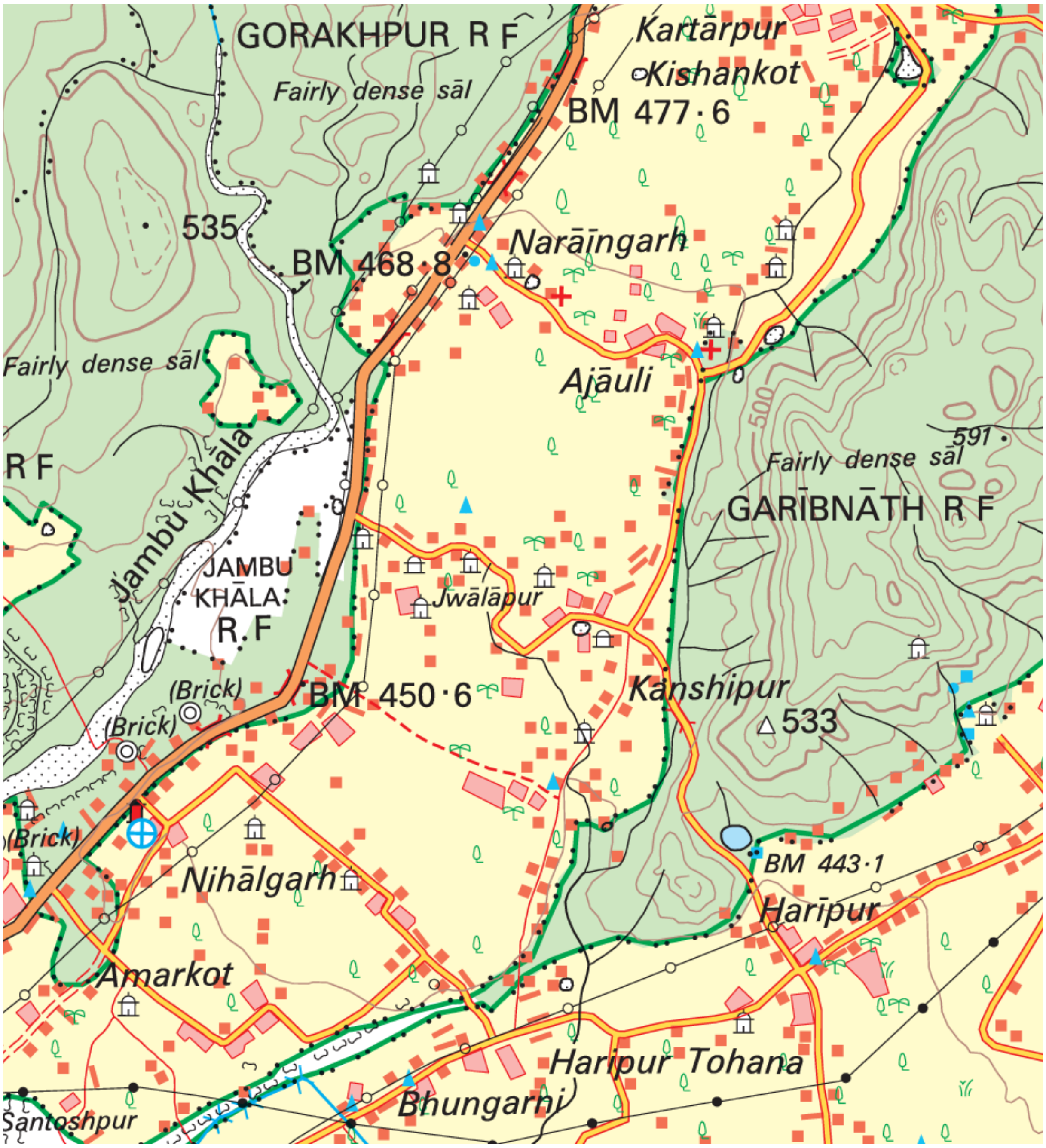



*Figure 4.12 (d) Sample regions of Indian Topographic OSM 53F11-Region 1*

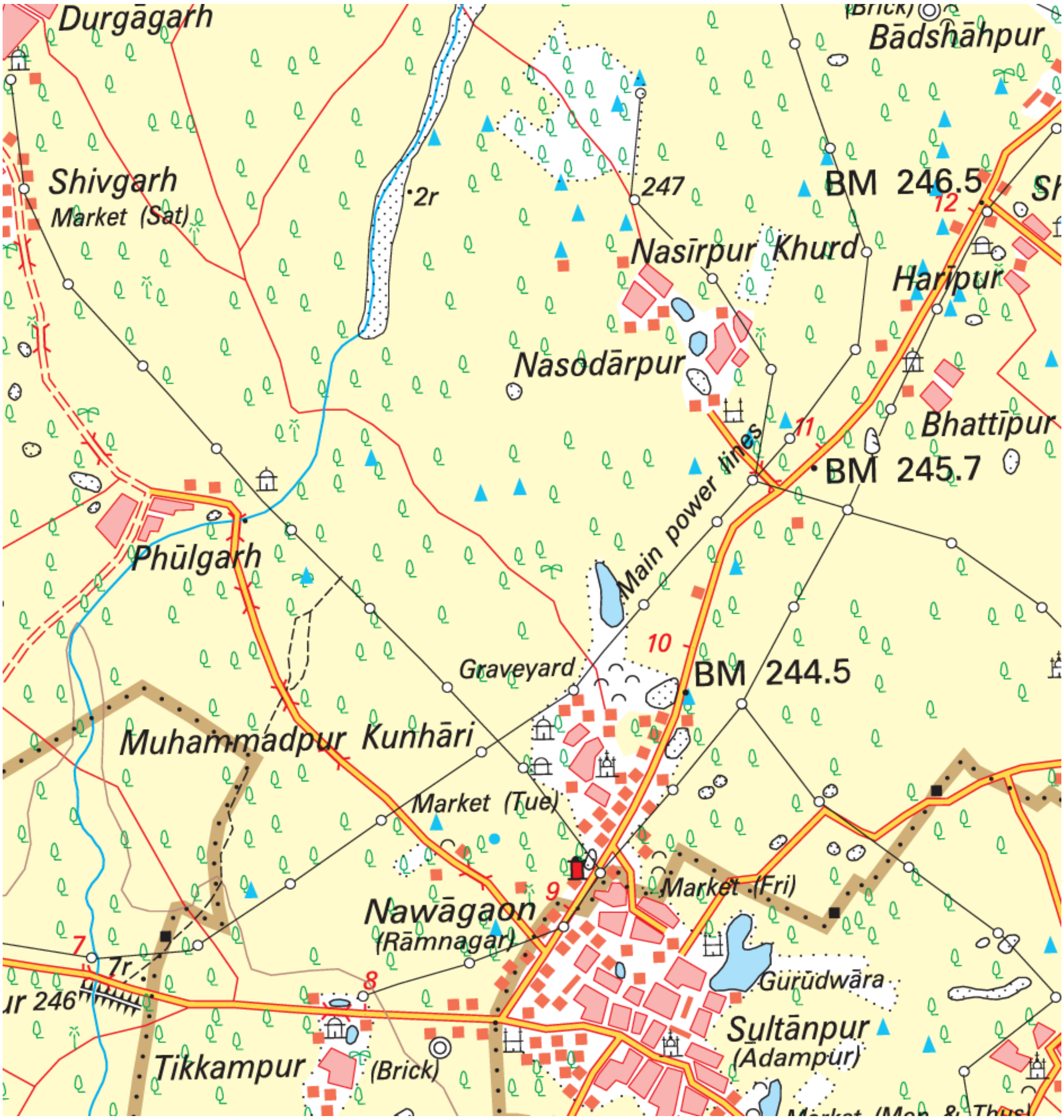



*Figure 4.12 (e) Sample regions of Indian Topographic OSM 53K1-Region 1*

## 4.7 DISCUSSION

The framework that has been proposed for the development of the Indian topographic map understanding system uses the integration of functioning of the techniques like image processing, pattern recognition, and adaptive Neuro-fuzzy inference system. The proposed system performs operations like a human map reader. This concept facilitates many operations like legend's shape and their pattern recognition;initial legend knowledge creation without human expert or human intervention; map segmentation; use and evaluates existing knowledge and adapt it recursively like the human brain and has to be implemented with proposed approaches described in this chapter. The scope of the proposed system towards the development of an automated Indian Topographic Map Understanding System (ITMUS) has been characterized by the development of a system for an understanding of legends in Indian topographic map. It has been proposed that the system should facilitate the understanding of different layers of the Indian topographic map. The instantiation of topographic map objects into an object oriented framework has been proposed for better understanding such as from object instances to concept or semantics and from simple to more complex layers. The proposed approach would combine feature based and initial domain knowledge driven learning based classification in order to retrieve and understand map objects and layers of a multi-temporal series of topographic maps. Thus, the analytical method for detection of map object's semantic meaning in an operational way has been proposed to develop a method based on the data model for retrospective topographic map analyses either land-use wise or category wise. The proposed system would be validated on five GeoTiff Open series Indian topographic maps (in the scale of 1:50,000) prepared by the Survey of India, Dehradun. Thus, the implementation of the proposed design for topographic map understanding can now be undertaken. Also, the existing work and methods had been tested on a few documents and different kinds of maps with different characteristics and quality, which have neither been significantly evaluated nor been compared. These systems have failed to give the complete map understanding solution. In current research work, the aim is that to use human understanding as objective criteria for map object understanding and information extraction from the topographic map which has to be subjected to different measures of performance evaluation. The system would be assessed in terms of the accuracy, completeness and efficiency.

# CHAPTER 5 DEVELOPMENT OF THE SYSTEM

## 5.1 INTRODUCTION

Automated understanding of topographic map has been a very complicated task, so attracts the attention of many researchers. Many researchers [152, 154, 332] have found that the understanding process cannot be made automatic and requires interactive techniques and knowledge. However, in current research work, an attempt has been made to summarize and develop main principles that could be used as a basis for constructing an automated topographic map understanding technology. To achieve the objective of topographic map understanding through emulation of the human map understanding process [195, 197], a fully automatic, legend driven hybrid approach consisting of feature based technique with the adaptive learning capability has been adopted. Simultaneously, simple image processing operations have been carried out to separate map layers for the map object recognition task. The initial fuzzy inference system and learning techniques have been used to make explicit rules from a legend feature dataset. The learning technique enriches the map object feature dataset in spite of their spatial variation and vague numerical shape and structural feature vectors which have been affected by heavy interconnectedness and overlapping conditions. In this research work, a hybrid method combining the shape and structural feature vector based approach for pattern description and adaptive Neuro-fuzzy classification has been developed to devise a human based topographic map understanding/reading mechanism in a machine. Here, the sub-goal is to avoid human intervention in initial knowledge implementation and to enable effective map layer separation and more general object description methods to make the system robust. The approach developed has been different from those reported in the literature. In the developmental approach, the Geospatial information has been extracted from OSM Indian topographic map images and interpreted maps (i-map) with annotation have been displayed for map symbol understanding purpose.

The development of automated topographic map understanding system is consisting of segmentation of topographic map image, also learning the feature descriptors as representative properties of a group of objects distinguishing a specific map object category and classifying the new object as a possible member of the class by comparing its common properties to those of the set of objects [29, 31]. Mainly, the topographic map understanding system must include processes for analysis and interpretation of relevant information from the map and must produce the Geo-location based interpretation of topographic map as well as an understanding summary to the user in an appropriate format [13]. The proposed system has to separate the map into the constituent's objects, exhibiting common characteristics based on the shape and structural attributes. All these processes in map understanding system should be based on knowledge acquired from legend understanding instead of processing the data and finding object patterns in the region of interest on the map. This approach will help in minimizing the cost of computation, which is important for an efficient system. An automated system has been proposed which emulate the human learning and understanding of maps, visualized as a solution to the problem of automated understanding of topographic maps and extraction of thematic layer information. Section 5.2 and its subsection describe Indian topographic map understanding system's architecture, module manipulation, and processing. The development of Legend understanding subsystem (LUS) has been described in Section 5.3 along with description regarding the development of acquisition and preprocessing module, color coding module, feature description and identification module, shape, structure rules and recognition, legend interpretation, implementation are provided. In section 5.4, brief information about the development of Map understanding subsystem (MUS) is reported. In the subsection 5.4.1, initial FIS design and initial legend training data set are provided and in its subsections, learning module implementation is described, while Object-Oriented Data Model is discussed in subsection 5.4.2. Further, Map geo converter implementation is given in subsection 5.4.3. In the next subsection 5.4.4, Preprocessing Module implementation is discussed, whereas in its subsections the sub-modules like RGB and Gray Index Thresholding, Layer Segmentation, Gap Filling and Layer Reconstruction algorithms are described. While statistical shape features extraction method is briefed in subsection 5.4.5, whereas in its subsections the map object description has been reported. In subsection 5.4.6, Map Understanding Subsystem Kernel is discussed and its subsection provides FIS Design, MUS Kernel Design, learning module implementation details, evaluation Of ANFIS to select the best model for final MUS, Goodness of the ANFIS is checked before incorporating it in MUS kernel successfully. Subsection 5.4.7 gives map representation module implementation details whereas Map Layer Analysis Module is discussed in section 5.4.8. While Map Spatial Analysis Report Generation, Map Symbol Accuracy Assessment, Map Layer Comparison, and Accuracy Assessment are described in sections 5.4.9, 5.4.10 and 5.4.11, respectively. Lastly, implementation and functioning of the modules have been described in section 5.5.

## 5.2 INDIAN TOPOGRAPHIC MAP UNDERSTANDING SYSTEM (ITMUS) ARCHITECTURE, MODULE MANIPULATION, AND PROCESSING

Topographic Map understanding can be defined as one of the problems solving that involves recognizing and annotating/naming topographic map objects. Generalization, specialization, schematization, visual abstraction and image processing principles have been inherited during the whole development of legend learning and map understanding by machine. In the system, the geospatial information extraction process which consists of learning and legend understanding comprises every possible reference between semantic meaning of legends/map objects and geography of the objects has been represented by itself. However, the manual process is used in the Survey of India for generating Meta knowledge of the Geo-referenced topographic map. It is highly labor intensive task, which further highlights the need for automated building of digital repository containing map information database and automatic information extraction. It has been still in progress for many geographic areas in India. Standard meta-knowledge containing the information depicted on the map and which is connected to semantic descriptions of spatial information has been used as a reference data to evaluate the system performance. The three basic key rules have been identified to be significant to devise a proposed map understanding system. They have been shown in Table 5.1.

***Table 5.1Key rules and its content***

| **Key Rule** | **Contents** |
|---|---|
| Color / Color Tone Criterion | e.g. Color code for Red, deep red, bright red, green brown, etc. |
| Nature of Shape | Empty, Filled, structure etc. |
| Geometric Parameters | Area, Eccentricity, Solidity etc. |

The proposed automated Indian topographic map understanding system has been characterized by four development phases viz Physical phase (space), Measurement phase (space), Feature phase (space) and Decision phase (space). The phases and their interactions have been described as A physical phase has been characterized by reading georeferenced topographic map legend/map in physical space which enables to represent it numerically by some measurements constituting measurement space. Mapping from measurement space to feature space is observed in Feature selection and extraction phase [314]. The object has been projected as a property of a geographical entity. The knowledge set is implemented using shape and structure features. Decision phase has constituted inference ability for making the decision for classifying and understanding map object. The building blocks of proposed system have been shown in Figure5.1.

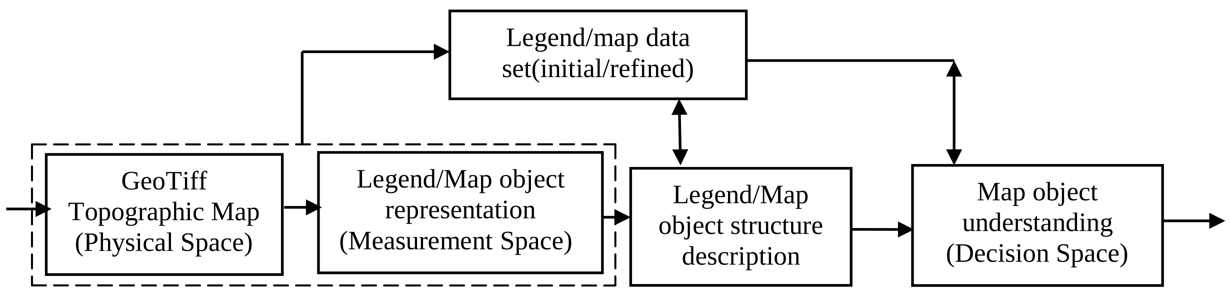



***Figure 5.1 Schematic Representation of proposed automated Indian topographic map understanding system [106, 234]***

### 5.2.1 The Architecture

The ITMUS with 6 layers of abstraction and hybrid control architecture has been developed. Usually, in the image understanding, three levels of abstraction [110] have had to be admitted. First: Low level, which deals with the knowledge about image processing; Second: Intermediate level, which contains the knowledge about the transition between numerical and symbolic data and Third level: High level, which contains all the domain specific knowledge like semantic meaning. The image processing model demonstrated in section 3.4.1, have been broken down into a layered architecture which has been developed and found useful in the extraction and interpretation of map symbols. In this section, the layered architecture of ITMUS system has been discussed. Each level of abstraction corresponds to an independent module as described in Figure 5.2. Bottom level (Level 0) corresponds to topographic map/legend data; Level 1 contains set of generic descriptive structure which has been used to describe complex legends from legend set; Level 2 and Level 3 shares a recognition task which performs mapping of the extracted structure onto symbolic concepts. According to the complexity of legend structure, the task has been composed of several subtasks. The role of Level 4 deals with the processing of the map in an intelligent way, i.e. by a program of intelligent classifiers. Level 5 provides a platform for user or client, to deal with the various functionality of ITMUS and obtain a retrospective analysis of topographic map in the form of annotated map region, thematic map layers, geo-location based map or layer dataset. The successive combination of modules according to levels which have been given in architecture would lead to the representation of annotated topographic map.

### 5.2.2 Module Manipulation and Processing Overview

In the study, the potential of an object based map analysis has been used to mimic human way of topographic map reading/understanding. The system development flow as shown in Figure 5.3 has also been illustrated in Appendix I along with the pseudo code. Color based legend identification has been applied to GeoTIFF raster topographic map legend set. First, a color coding scheme (Table 5.2) has been developed to decipher map legends into categories based on their colors. All legends have been processed by image processing routines and further their structural features have been calculated.

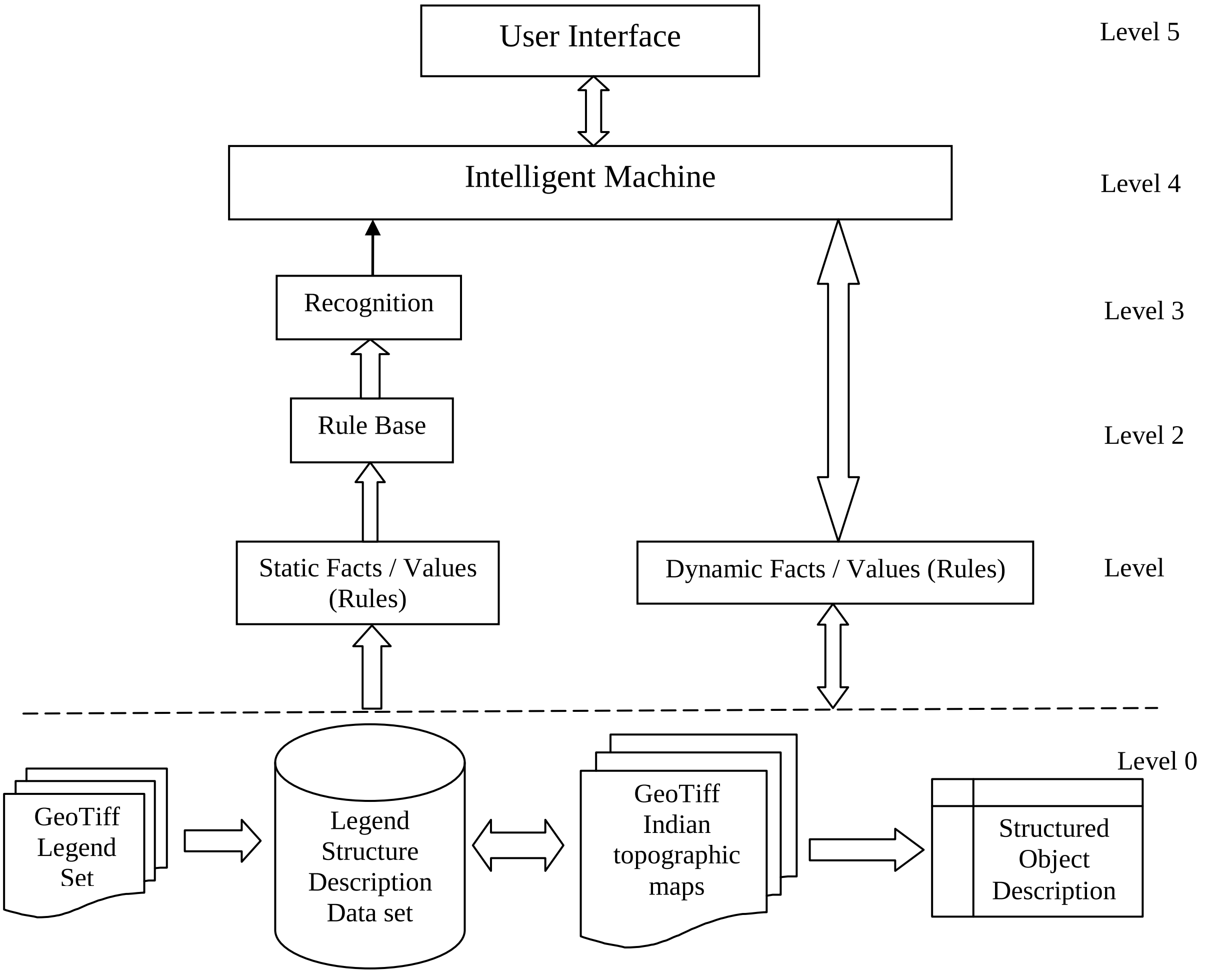



***Figure 5.2 6-Layered architecture of Proposed Topographic map understanding system***

***Table 5.2 Color code estimation scheme for legend analysis***

| **Input** | **Legend** | | | | | | |
|---|---|---|---|---|---|---|---|
| **0-255** | **Black** | **Blue** | **Green** | **Red** | **Brown** | **Yellow** | **White** |
| | **Bl** | **B** | **G** | **R** | **Br** | **Y** | **W** |
| **Color Code Book** | 000 | 001 | 010 | 100 | 101 | 110 | 111 |

The same approach has adopted with map understanding where the process for separating foreground and background and assign color code is to be implemented. Then, the objects carrying a same color code, but exhibits different features reduce the search space in map understanding method. Thus the system enables the object in different color layers to be described by their structural and geometric features in an operational way. The achieved representative features of map legends have stored in legend knowledge base. Five legends sets of five different topographic maps of five landscapes have been used to obtain representative features describing the legends. This knowledge base, have used as an initial training set to generate initial rules of the fuzzy inference system. It has been further used to train, evaluate and tune rules using the adaptive Neuro-fuzzy model. The method used for the development of Indian topographic map understanding system, have been characterized by the following steps:

1. Selection of 'legend sets' as an input to the legend understanding kernel;
2. Pre-processing the legend set, Separation of layers based on color;
3. Extraction of objects and calculation of their geometrical parameters such as solidity, number of holes, area etc.;
4. Classification of objects based on the processing of simple primitives, geometrical parameters, and their interpretation. Static rules contain geometric parameters such as antecedent and semantic (i.e. Meaning) of legend as a consequent. The result of the algorithm is used for knowledge implementation, which is initial crude domain knowledge of map understanding kernel. This domain knowledge is a special data structure which contains information about recognized legend and their structure/geometric parameters and annotation;
5. Assignment of unique code to Topographic map entities which have been provided as the target output for ANFIS classifiers;
6. Configuration of ANFIS classifiers of Sugeno-type, from an input data selection (Nine ANFIS classifiers have been intended to classify topographic entities, including characters and text), the number of membership functions, the type of input membership functions and/or the type of output membership functions;
7. Training of ANFIS classifiers;
8. Map preprocessing, layers separation and formation of structure description of objects;
9. Evaluation of ANFIS on topographic map object description;
10. Further training of classifiers on increased training data set until generalizes the solution properly or become stable.

All methods mentioned above are described in subsequent sections.

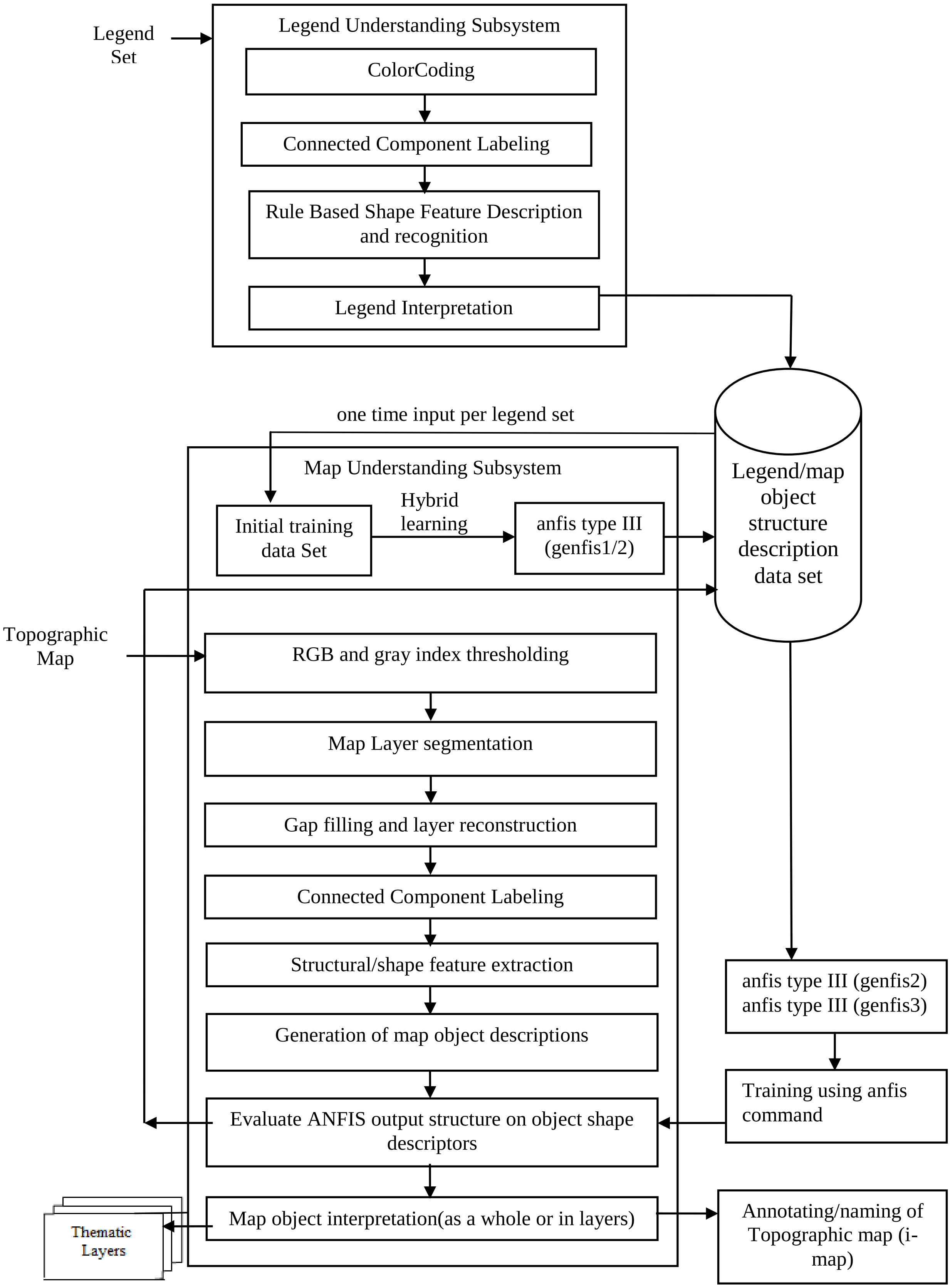



***Figure 5.3 Flow graph of the Indian Topographic map understanding system (ITMUS)***

## 5.3 LEGEND UNDERSTANDING SUBSYSTEM (LUS)

The method devised here has been relied on human map understanding process or approach in which the map legend understanding has been a prerequisite for topographic map understanding. The Legend understanding kernel provides a way for extraction and reorganization of symbolical objects in the maps. A feature is a data unit which represents a geographical entity. The features referred here is different than that used in pattern recognition. The entire work done in LUS has been divided into five phases and the depicted using flow graph shown in Figure5.4. The phases involved in the development of LUS have been briefed below.

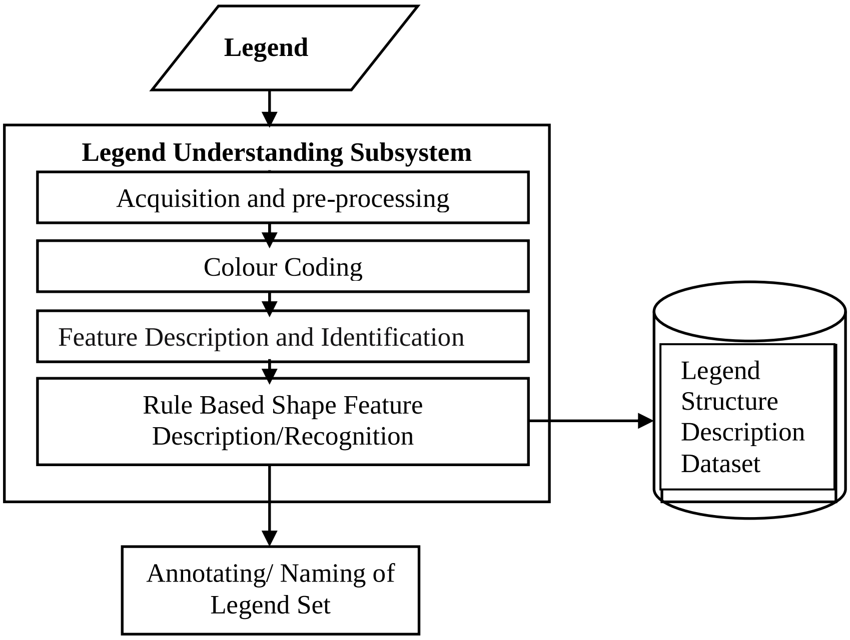



***Figure 5.4 Flow graph of Legend Understanding subsystem (LUS)***

(1) *Acquisition and Preprocessing*: Conventional signs provided at the bottom of the topographic map have been located by the program and cropped for legend analysis and understanding. From these legend sets, each legend row has been read programmatically to recognize symbol in it. These small search regions have been selected for processing.

(2) *Color Coding*: Based on RGB values, the legend set has been categorized into its constituent layers as vegetation, water bodies, man-made structures and text as reflected in green, blue, red and black colors respectively. The color code has been assigned to each legend.

(3) *Connected component Labeling:*

(i) *Feature description and Identification*

(ii) *Recognition in terms of shape*

This is the most significant process for feature recognition of objects in binary map images. These images have been selected to process by the morphological operations and geometrical structure measurement which constitute the legend. Several algorithms have been developed to recognize the shape feature of each object. The partial taxonomy of topographic map legends has been illustrated in Figure 5.9.

(4) *Legend analysis and recognition:* Rule-based legend recognition has been developed.

(5) *Interpretation:* Repository Containing Recognition Result and Feature Description has been generated for making the results of recognition phase useful and also for creating input to MUS. Also, legend set has been annotated with semantic meaning of respective legends by LUS.A detailed description of above phases has been described in the following sections. The LUS have been implemented to understand legend set given from the topographic map. It reads legends from 'legend set'. Afterwards, it is using the knowledge to recognize objects that might not be directly depicted on the map in the same form as found in legend set, but it succeeds in perceiving it through the formation of their location and shape in nature.

The flow graph of methods devised in Legend Understanding Subsystem Kernel has been shown in Figure5.6. .A human being also gains understanding about the map legend/object by establishing correspondences between mental knowledge (brain phenomenon) and their formal description (mind phenomenon) adaptively [230]. In this research work, the map reading and understanding approach which based on legend understanding has been a prime objective, which attempts to emulate human understanding using sophisticated computer programs. These programs have been designed to acquire, process, store, use legend information and adapt acquired information according to various conditions. Hence, a Legend understanding subsystem is developed which helps the machine to develop the understanding about the map legends as a representational medium and assign their semantics as well as spatial knowledge encoded therein in the map. The flow graph given in Figure5.5 describes the steps required to implement LUS kernel, which has been explained in the context of sub-modules in the next subsections.

### 5.3.1 Acquisition and Preprocessing

In the legend understanding subsystem kernel, the extraction and labeling of various disjoint and connected components in legend set image have been considered to be central. Legend region has been selected and blob analysis has been performed. Further, based on pixel connectivity, the scanned legend areas by connecting components labeling process grouped its pixels, i.e. connected component pixels have an equal pixel value. After, determining all the groups, a gray level or a color has been assigned to each pixel. In order to recognize connected pixel regions, pixel by pixel the image has been scanned from top to bottom and left to right. The map has been scanned by moving along the row till the desired point *p* (where *p* indicates the pixel which is labeled at any stage in the scanning process) for which *V*= {1}. This condition gets satisfied means, all four neighbors of pixel *p* i.e. The neighboring pixel(a) to the left of *p*, (b) above it, and (c and d) the two upper diagonals gets examined which have already been encountered in the scan. The labeling of *p* has been occurring based on the following conditions as follows:

- If all four neighbors are 0, a new label will be assigned top, else
- If only one neighbor has *V*= {1}, label, p will be assigned, else
- If more than one of the neighbors have *V*= {1}, assign one of the label's top and make a note of the equivalences.

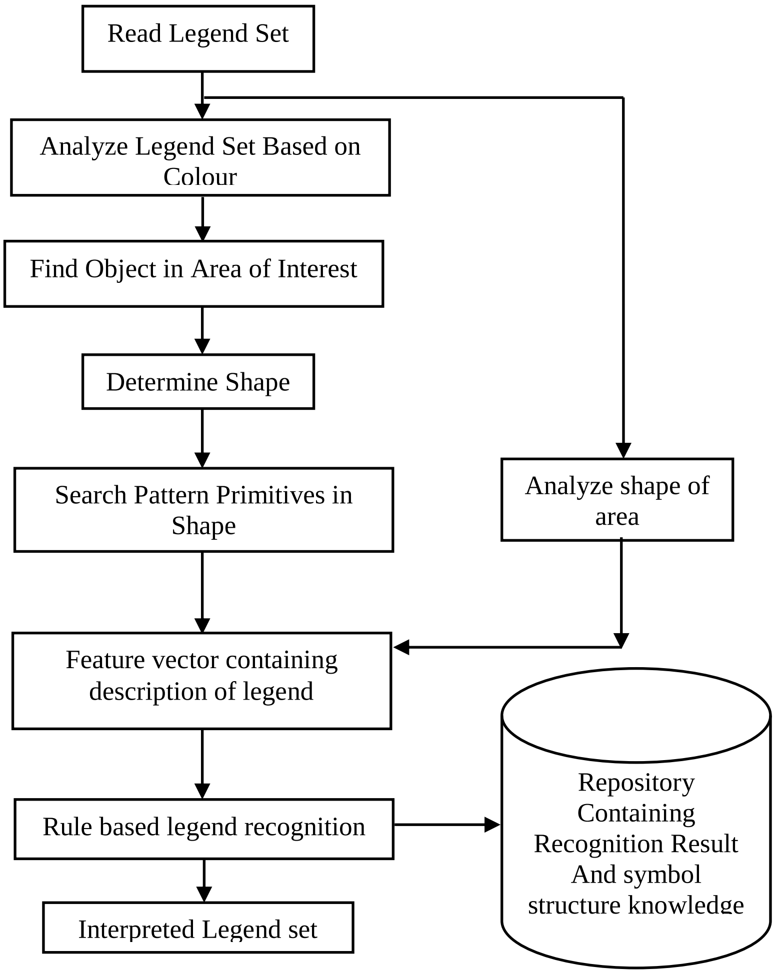



***Figure 5.5 Flow graph for the development of Legend Understanding Kernel***

After the scan of legend region, same label pairs have been arranged into equivalence classes and each class is assigned by a unique label. In the final step, the legend selection area is scanned once again; where the labels have been replaced by the label of its equivalence classes [6, 16, 294].

Now based on the ‘min’ and ‘max’ operations, binary morphological operations acting on binary images have been employed. Erosion of legend has been carried out by assigning each pixel to the minimum (or maximum) value found over a neighborhood of the corresponding pixel in the legend selection area. However, the flat structuring element in the binary case, predicts the neighborhood. In the gray scale legend, the structuring element has been used for specifying the desired local gray-level property [110]. As the maximum (or minimum) has been calculated in the neighborhood, the structuring element value is also getting changed (added/subtracted). The grayscale dilation of *'f' by* structuring element '*b'*, denoted by'$f \oplus b$', is defined as,

$(f \oplus b)(x,y) = max\{f(x-x',y-y')+b(x',y')\ D_b\}$ where $D_b$ is the domain of *b.*

Next, the structuring elements have been created for extracting object component in legend selection area and filling the holes. The structuring element, SE = strel ('disk', radius, Number of neighbors) creates a flat, disk-shaped structuring element. Based on a number of neighbors, the disk-shaped structuring element has been approximated. No approximation is required when a number of neighbors equals 0 and centers of all pixels of the structuring element members are less than radius away from the origin. Next, the origin of the structural element has been translated to possible pixel locations in the legend set and compared with the underplayed image pixels. Whenever foreground and background pixels in the image are getting matched exactly with respective image pixels in the structuring element, the image pixel below the origin of the structuring element has been set to background (zero) [24, 319]. Once foreground legends are separated, the 45° convex hull algorithm will be applied to determine the region of legend. As the color of the image transformed into the gray, the linear objects have been extracted more accurately because the gray value shows limited relative to the chromatic values and not confusing excessively [150]. The linear object pixels show less value in the gray image as that of the background, so separation has been done easily by thresholding.

### 5.3.2 Color Coding

Based on color statistical processing and color neighborhood analysis, color separation algorithm has been developed [189]. The statistical data include parameters such as color histogram, quantity, etc. in the image. Development of this module consists of several steps. First, all map legends have been separated in distinct color layers based on a color coding technique from the input image. The input image has been transformed into a gray version for extracting linear objects as well as cell objects by using gray level histogram index analysis. Second, the resulting binary images have been filtered, thinned and pruned to generate clean masks of one-pixel thick line [226]. Then, the different cases of gaps have been found out and served as seeds and grow to repair the legend segments [239].

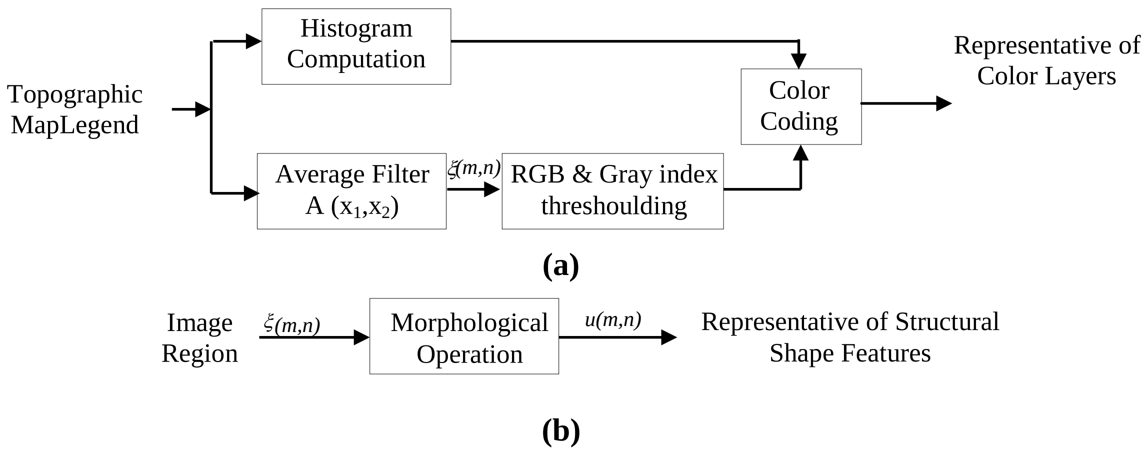


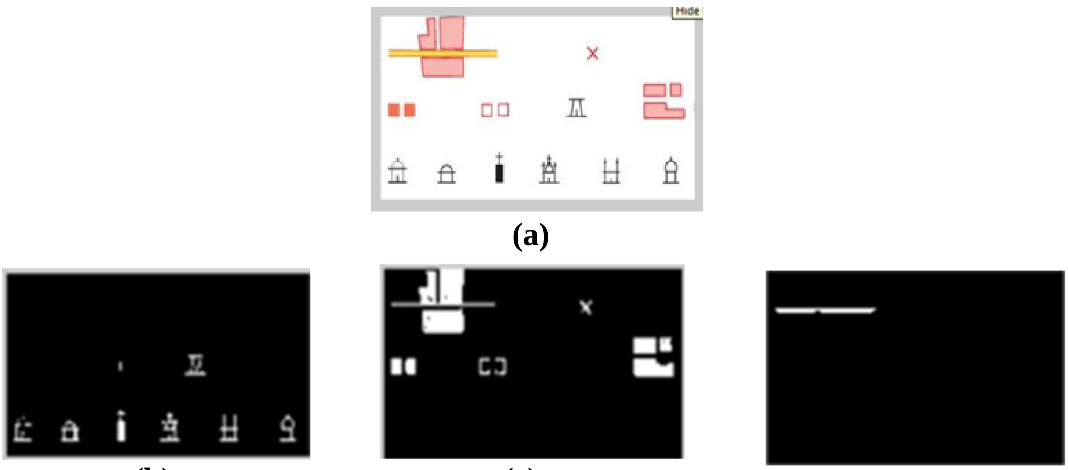

***Figure 5.6 (a) Module architecture for representing color coding and (b) computation of representative structural shape features***

The developed method has two contributions: developing a color based layer separation technique and introducing a feature extraction process from the gray version of the input legend image. The module architecture is shown in the Figure5.6. This section describes the proposed color layer separation module. It is proposed to segment layers based on combined key assigned by RGB and gray level thresholding. The proposed color scheme is regarded as 'Color code book' to emphasize the use of the color code with the feature extraction scheme. Weight matrix has been calculated based on the foreground and background colors in the merge/overlapped region [162]. In particular, at a point in the region, the foreground is calculated as a weighted sum of the pixels on the perimeter of the known foreground region. The nearest pixel is assigned the weight to 1 and this weight will decrease linearly with distance and reach to zero for the pixels located at twice the distance as that of the nearest pixel. For initial estimation the background based on nearby known background pixels, same procedure has been used, which is refine or overlook later by the geometrical feature extraction. The generated color code has been given in Table 5.2. From Figure 5.7, the color code generated for black legend have been measured as 000. This combined color key obtained through RGB and gray level thresholding. The Part of Input legend set, and it's transformation into representative foreground layers is shown in Figure 5.8. The boundary pixels supposed to be defined as foreground pixels (1) or background pixels (0). For foreground pixels (e.g. A red outline), the true colors are used for defining the boundary conditions, while for background pixels boundary conditions are defined by initial estimation of foreground colors in the color code book. The estimates are shown as the color code book in Figure 5.7.In legend set, holes/gaps are depicted due to nonuniform colors. To fill up these gaps ‘k nearest neighbor algorithm’ is used. This algorithm considers a number of neighbors, distance between neighbors and the angle between neighbors to fill up gaps. Also, in multi-color objects, gaps are found, when the layers are extracted based on their R, G, B values. In legend set processing, gaps usually do not have an impact on measuring statistical characteristics or structure primitives measures.

**Color code book**

```
    r = img(ii,jj,1);
    g = img(ii,jj,2);
    b = img(ii,jj,3);
Black
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
if r < 110 & g < 110 & b < 110
                a = 0;
                b = 0;
                c = 0;
elseif r == g & g == b & r < 200
%     elseif  (abs(r-b) <= 5) & (abs(b-g)<=5)  & r <200
                a = 0;
                b = 0;
                c = 0;
%Then
%resolve color
            a = Out(i,j,1)/255;
      b = Out(i,j,2)/255;
      c = Out(i,j,3)/255;
      R_Out(i,j) = a*100 + b*10 + c;
```

***Figure 5.7 Sample of color code book***



**(a)**

**(b)** **(c)** **(d)**

***Figure 5.8 (a) Part of Input legend set, and it's transformation into representative foreground layers (b) Foreground black layer, (c) Foreground red layer, (d) Foreground yellow layer***

### 5.3.3 Feature Description and Identification

Mathematical morphology has been investigated from the mathematical viewpoint and used as an important technique for image processor [67, 70, 281, 333, 334]. In the development of the system, mathematical morphology acts as a set of neighborhood operations of the topographic map image. Erosion and dilations have been applied as starting operations in the system. Cartographic symbols have more complex structure than any image or document containing characters and also the located at different places with different orientation and scales, or be in a relationship with each other etc. Therefore, recognition of cartographic object recognition is very complex and work is going on for an accurate solution. A group of cartographic objects includes various symbols, characters, and texts, etc. The preliminary task is to represent legend in the form that the computer can read and understand. Every legend may be characterized by two parameters; color and shape. The shape can be instantiated by some characteristics, which exhibits such as empty, filled and structure, or polygon, single or multiple. The same has been shown in Figure5.9 by a partial taxonomy of legends. Mathematically, “line” can be distinguished from the character or numbers by applying the criteria of the ratio of width/height. A segment which is having a length longer than character width/height is line object. However, it is difficult to distinguish points and lines systematically as conventional erosion- dilation operations extract objects based on connectivity. The iterative directional erosion technique has been used for detection of long lines as the segments of long lines are conserved. Then, all short lines are erased by n iterations of directional erosion-dilations [333]. Several researchers [1, 5, 38, 178] reported their work of recognition of various sets of cartographic symbols. The main requirement of these approaches is that the map symbols should be separated from the rest of the graphics. The recognition starts after the separation of symbols. The main approach used to recognize map legends includes a symbol, text, and character.

A recognition technique based on shape described by Elliman and Sen-Gupta[93] using the following shape features:

1. Color of symbol centroid
2. Circularity
3. Number of holes
4. Number of sides
5. Number of lids

This approach has been tested on a set of cartographic symbols [93]. The same principle to some extent has been used in the proposed system to develop a structural feature description module. It holds the logic and the algorithm to form the symbol description. The structural feature based model has been developed in which all varieties of the object's description have been made possible by extracting and integrating different features such as shape and color. Shape descriptors have been formed using quantitative measurements of the shape of an object using the shape profile of the legend and its physical structure. This module has been responsible for the measurement of shape profile and derivation of feature descriptor with Color features and 10 invariant geometrical shape features such as branches, end points, euler number, solidity, orientation, major axis, minor axis, eccentricity, area, and centroid. The feature extraction method has been used to extract image components useful in the representation and description of the region such as branches, shape, and convex hull irrespective of its type. Most of the literature emphasizes the extraction and recognition of specific map symbols and devised an independent algorithm for its recognition. But a general methodology capable of providing the semantic understanding has been used to understand map symbols depicted on the map.

In the present system, the processing thread/unit called LU-Handler has been devised as a backbone of the symbol description to generate geometrical feature vector. The map image region has been transformed in shape and structure features vector by performing various morphological operations and connected component analysis. The steps correspond to the mathematics for converting it into a feature vector. The first step has been adopted to determine the number of components in legend region. The second step consists of performing bounding box operations on each component. The symbol or part of a symbol inside the bounding box has been processed to count the number of pixels in the symbol region to determine the point, linear and area objects. Further, properties of the pixel region have been computed in terms of eccentricity, solidity, area, centroid. Next, the ratio of perimeters of the convex hull over that of original symbol boundary has been defined as convexity. Shape Feature Descriptors and their computation have been reported in Table 5.1. Basic features of minimum bounding box circumscribing the normalized boundary of objects in image region have been obtained as follows:

Height (Major axis): It is a length of the minimum bounding box. The length is normalized using

NL = L/LF where LF is the length of the framework.

Width (minor axis): It is a width of the minimum bounding box. The width is normalized using NW = W/WF where WF is the width of the framework. Area: Area of the minimum. the bounding box is NL X NW

Further, Logical/tentative (not actual) shape of the object in the image region has been used to determine extrema future. The extreme points in the region are described by a matrix of size 8 × 2 in which each row represents the X and Y coordinates of one of the points. The generated vector have consisted of coordinates of top-right; top-left; right-top; right-bottom; bottom-right; bottom-left; bottom-left top. The function bweuler as all = bowlers (BW, n) has been used for getting the Euler number for the BW binary image. The total number of holes in the objects has been subtracted from the total number of objects in the image for Euler number. Here, 'n' specifies the connectivity. Legends or objects possess connected sets of 'n' pixels, where, pixels having a value of 1. The region prop measure properties of connected sets off on pixels and measure the set of properties specified by an argument of bwconncomp for each connected component (object) in CC. The connected component, CC has a structure returned by bwconncomp [12]. Two-dimensional filter has been created by fspecial ('average'). The fspecial creates 'H' as a correlation kernel, which uses an appropriate form to use with imfilter [16, 133]. Thus, feature extraction and measurement has been done in each legend region and have been used in rules to deduce the semantic meaning associated with legends. Figure 5.6b shows a block diagram of feature extraction whereas detail procedure has been given in Table 5.3.

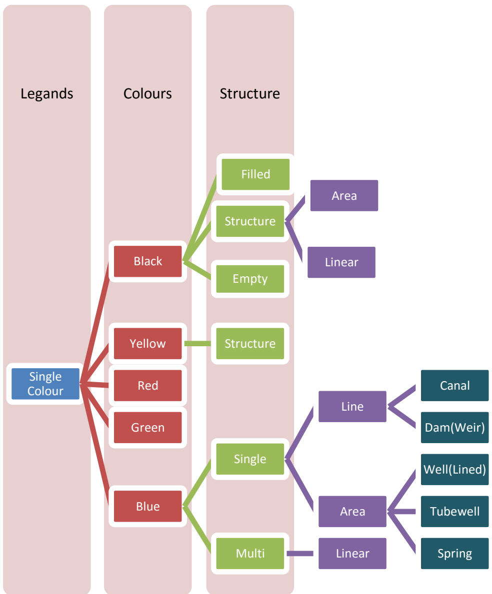



***Figure 5.9 Partial Taxonomy of Topographic map legends***

### 5.3.4 Shape Structure Rules and Recognition

Shape features and their structural parameter have been calculated to define feature description of each legend. Here, segmentation and recognition have been done simultaneously. After, feature extraction and measurement has been done, in recognition, each feature value and combinations of it have been checked against the rule to derive legend's meaning. There are many ways to implement rule-based classification and inference system, but static rules have been adopted to derive the semantic meaning of the legends of topographic maps. Among many categories, rule based segmentation and feature extraction approach have been used so as to model them in the form of rule, based on application dependent heuristic knowledge. In this case, the process of existing threshold based segmentation has been used for gathering the heuristic knowledge while feature extraction methods have been used for building the initial legend structure knowledge base.

***Table 5.3 Shape Feature Descriptors and their computation***

| Sr. No. | Features | Details | Mathematical Morphology |
|---|---|---|---|
| 1 | Branches | Gives the number of branch points in the object structure | Morphological operation on binary image |
| 2 | Endpoints | Gives the number of end points in the object structure | Morphological operation on binary image |
| 3 | Euler's Number | It gives the relation between a number of continuous parts and number of holes in the object. | If S and N represent continuous part numbers and whole numbers respectively, then, Euler number defined as: Eul = S - N |
| 4 | Shape | It is determined based on extrema | Rule based normalized extrema value comparison e.g. `ifnorm([STATS.Extrema(,), STATS.Extrema(,)] - [STATS.Extrema(,), STATS.Extrema(,)])<5 then shape= 'Triangle'` |
| 5 | Solidity | Describes convex or concave shape | Solidity $=A_o/ H$ Where, $A_o$Defines the area of the shape region while H represents the convex hull area |
| 6 | Orientation | Describes angle between the X axis and the major axis of the ellipse | `Theta = Orientation`<br>`If theta > 45`<br>`Then rotate (image region, 90-theta);`<br>`Else`<br>`Rotate (image region, theta);`<br>Calculated by region property. |
| 7 | Major axis | It is the length of the minimum bounding parallelogram | NL=L/LF |
| 8 | Minor axis | It is the width of the minimum bounding parallelogram | NW=W/WF |
| 9 | Eccentricity | The ratio of the distance between the foci of the ellipse of a symbol to its major axis | Its value varies from 0 to 1. |
| 10 | Area | The area of minimum bounding parallelogram | A=NLXNW. Gives the actual number of pixels |
| 11 | Centroid | Centroid $g_x, g_y$ | $g_x=\frac{1}{N}\sum_{i=1}^{N} x_i$<br>$g_y=\frac{1}{N}\sum_{i=1}^{N} y_i$ |

Firstly, shape and structural parameters of the legend have been measured and then the legend has been recognized by conditional rules. As shown in Table 5.3, the structure description is formed according to legends shape measurements. The brief step by step method has been given below:

1. Divide each row into parts.
2. Perform segmentation in each part based on RGB values.
3. If nothing is found in part then returns the color as empty.
4. If it returns some color code (value) then find what legend is inside of that part.
5. If anything is found in the part then determine how it is and in what numbers.
   a. Perform blob analysis
   b. Find convolution hull.
   c. Perform morphological operations.
6. How it is meant to determine / recognize shape parameters of object found in crop part
   a. IF the number of pixels constituting legend is less than or equal to 4 THEN it is point.
   b. The row and column are points for branch and end positions.
      IF $r_b$ is 0 then $r_b$ and $r_e$ are zero, then it is 'circle'.
      IF $r_e$ is two, then it is 'line'.
   c. Calculate theta by subtracting endpoints and dividing it by 2.
   d. IF $r_e$ are 4 THEN lines= 2
   e. IF $r_e$ greater than 4 THEN lines $=r_e/2$. Calculate the absolute value of endpoints.
      if it Less than or equal to 2 then F=0
      ELSE F=1
7. To recognize different objects having some characteristics common to them, intermediate description has been provided. For example, If "Black" pixels are greater than 1then intermediate description has been "multiple"black" which further recognized as "state boundary"," demarcated boundary" or "wetland" etc. based on another parameter like the size of pixels. The domain value for the size of the pixels will be {small<1-3>, large<greater than3>}
8. The axis ratio i.e. major axis / minor axis have been used to determine whether a structure is a dot or structure. For dot object, the ratio is small and for structure ratio is large.
9. Isolines have been recognized by thickness, length or type which are calculated by aspect ratio, major axis and number of even and odd type structure present in it.
10. In brown layer, for sand recognition, following steps have been adopted:

1. Load the legend image data.
2. Filter the image
    i. Create the filter (Gaussian [3X3])
    ii. Filter the data
3. Perform morphological close operation.
4. Find the region where local maxima occur.
5. Find the area, i.e. number of pixels
6. Write set of rules such as:
    i. IF no. of pixels greater than or equal to 3 THEN 'small' <res 'flat sand'>
    ii. IF no. of pixels are less than 10 and greater than 3 THEN 'medium' <res 'Sandhills'>
    iii. IF no. of pixels, or greater than 15 THEN 'dense' <res 'dunes'>

11. Average angle parameter (avgang) is used to determine the demarcated and demarcated boundary.

    IF avgang is less than 45 degrees THEN it is demarcated boundary

    ELSE demarcated boundary.

12. For "Black" color "Single" structure legends following calculations are carried out:

    axis ratio is equal to the major axis/minor axis

    The difference is equal to subtraction between major axis and minor axis

    IF axratio is less than equal to 3 & difference is less than or equal to 1 THEN legend is of cell type.

    ELSE IF axratio is exactly equal to 2 & difference is less than or equal to 2 THEN it is a rectangular cell.

    ELSE IF axratio is greater than 3 & difference is greater than 2 THEN it is a linear legend type.

    ELSE dot

13. The Euler number is used to decipher between filled, empty and structured legends. IF

    IFEuler's number is equal to 1 THEN res is equal to 'Filled'

    IF Euler's number is equal to 0 THEN res is equal to 'Empty'

    ELSE res is equal to 'Structured'

14. Now, once the process of acquisition of color and shape parameters as well as an intermediate description of the legend has been accomplished, then IF-THEN rules have been implemented to get legend description, which has been presented in consequent part. The rules have been formulated according to fundamental characteristics of legend structure.

### 5.3.5 Legend Interpretation

The method employs IF -THEN rules to parse structure and reduce feature parameter and primitives into legend description. The steps of IF-THEN translation have been illustrated by pseudo code of structure translation to legend description string for "Single" color "Single" structure object in Figure5.10. Shape parameters have been calculated by mathematical morphological operations and connected component labeling [110, 111, 135, 245]. Shape features and mathematical computation have been described in Table 5.3. After recognition, description obtained for legends and their respective features which have been stored in a legend's structure database as shown in Table 5.4. It has been required as an initial knowledge base for subsequent map understanding subsystem. Also, Legend set image has been provided by annotation string. Table 5.4 shows how legends would be represented in the dataset.

```
If Legend colorU  = black
      If axis ratio is equal to 1
      If euler number is 0 && solidity is 0
             then legend is Piller unlocated
            else if euler number is -3
            then legend is Mosque
      else if euler number is 0 and shape is triangle
      if  branches  is  3  &&  absolute  orientation  is
greater than 80
       then legend is unlighted buoys
```

***Figure 5.10 Sample Pseudo code for structure reduction to legend description string***

The LUS has generated the legend structure dataset, whose leftmost column contains the legend semantic meaning, the second and third column shows location information (which has been not shown here), the fourth column contains the number of branches, the fifth column gives the number of endpoints and a sixth column for the Euler's number feature. The last 5 columns show Shape, Solidity, Orientation, Height(Major axis) and Width(minor axis).This legend structure database has been used as the initial training set in MUS. MUS utilizes recognized legend set for initial rule extraction for building the fuzzy inference system and design of subsequent ANFIS's classifiers.

***Table 5.4 Sample table entries are generated as legend knowledge data set by LUS***

| Legend Description | branches | End pts | Euler no | Shape | Solidity | Orientation | Height | Width |
|---|---|---|---|---|---|---|---|---|
| Sand | 1 | 3 | 1 | 2 | 0.917258 | -63.3165 | 20.00008 | 21 |
| Sand | 0 | 2 | 1 | 2 | 0.930481 | -16.9648 | 29.50011 | 34 |
| Sand | 5 | 8 | -4 | 2 | 0.846959 | 5.159771 | 34 | 92 |
| Contour | 0 | 2 | 1 | 3 | 0.626866 | 84.27747 | 12 | 5.666665 |
| Contour | 0 | 2 | 1 | 3 | 0.661538 | 85.06767 | 12 | 5.666665 |
| Contour | 0 | 2 | 1 | 3 | 0.455446 | 1.487389 | 3.119996 | 25.00003 |
| Metalled Road Other | 0 | 2 | 1 | 2 | 1 | 0 | 2 | 73 |
| Village/Town | 0 | 2 | 1 | 2 | 1 | 78.3737 | 10.00032 | 9 |
| Metalled Road | 0 | 2 | 1 | 2 | 0.936242 | -0.53709 | 3 | 79.00001 |
| Metalled Road | 0 | 2 | 1 | 2 | 0.993671 | -0.08147 | 3 | 79.00002 |
| Metalled Road | 0 | 2 | 1 | 2 | 0.984241 | -0.36709 | 8 | 80 |
| Hut Temporary | 4 | 2 | 0 | 3 | 0.666667 | 45 | 4 | 1 |
| Hut | 0 | 1 | 1 | 2 | 1 | -45 | 6.000253 | 6 |
| Distance stone | 0 | 2 | 1 | 4 | 1 | 90 | 6 | 2 |
| Foot Path | 0 | 2 | 1 | 2 | 0.765579 | 0.132578 | 4 | 73.00002 |
| Bridge | 0 | 2 | 1 | 2 | 0.536842 | 0.806958 | 5 | 17 |
| Deserted Village | 4 | 4 | 1 | 2 | 0.450704 | 32.88874 | 11 | 11 |
| Buoys | 1 | 1 | 0 | 1 | 0.530612 | 87.7755 | 18 | 12.00001 |
| Char | 1 | 3 | 1 | 4 | 0.6 | 71.82146 | 17 | 10.54546 |
| Char | 0 | 0 | 0 | 2 | 0.680723 | 71.06056 | 16 | 11 |
| P O | 0 | 2 | 1 | 2 | 0.905063 | -87.1705 | 16.00009 | 8.933326 |
| Dispensary | 1 | 4 | 1 | 3 | 0.5625 | 0 | 11 | 11 |
| Arrow | 1 | 3 | 1 | 3 | 0.447853 | -25.1255 | 11.29426 | 19.76462 |
| Police Station | 5 | 1 | -2 | 4 | 0.964 | 55.53567 | 19 | 16 |
| Fort | 0 | 0 | 0 | 2 | 0.34358 | -28.4308 | 33 | 33 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Aerodrome | 11 | 13 | 1 | 2 | 0.589333 | 0.054091 | 9 | 93 |
| Hospital | 5 | 0 | -3 | 2 | 0.718266 | 65.43778 | 27.000 04 | 28 |
| Helipad | 4 | 7 | 1 | 3 | 0.526132 | -0.55647 | 24 | 54.3 |
| Scrub | 0 | 2 | 1 | 2 | 0.699187 | 2.501797 | 9 | 14 |
| TREES | 1 | 4 | 1 | 3 | 0.788618 | -32.1765 | 11.000 01 | 12 |
| Conifer | 0 | 2 | 1 | 4 | 0.861538 | -83.9365 | 19 | 7.0000 08 |
| Palmyra | 0 | 2 | 1 | 1 | 0.823944 | -70.265 | 18 | 8.2000 12 |
| TREES | 1 | 3 | 1 | 3 | 0.900763 | -45.1668 | 12 | 12 |
| TREES | 3 | 1 | -1 | 2 | 0.826347 | -77.8566 | 17.000 11 | 10.142 78 |
| Bamboo | 5 | 3 | -1 | 2 | 0.775 | 71.14975 | 16.000 18 | 13.749 92 |
| Bamboo | 4 | 2 | -1 | 2 | 0.855263 | 85.89845 | 16 | 13.625 08 |
| Plantain | 4 | 4 | 0 | 4 | 0.745318 | -7.35853 | 14.529 42 | 20.000 05 |
| Grass | 2 | 4 | 1 | 2 | 0.82 | -1.67977 | 13 | 19 |
| Grass | 3 | 3 | 0 | 2 | 0.806202 | 1.075277 | 13 | 19.000 06 |
| Grass | 5 | 3 | -1 | 2 | 0.801527 | -0.80149 | 13 | 20.000 01 |
| Palm | 1 | 1 | 0 | 4 | 0.884774 | -81.3393 | 20.000 02 | 14 |
| River | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| River | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 2 |
| River | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 2 |
| Tank | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 |
| Tank | 0 | 2 | 1 | 1 | 0.8 | 50.30983 | 2 | 2 |
| Tank | 4 | 8 | 1 | 4 | 0.724124 | -7.15259 | 27.261 56 | 95.000 05 |
| Boundary | 0 | 2 | 1 | 2 | 1 | 0 | 8 | 74 |
| Boundary | 0 | 2 | 1 | 2 | 0.973956 | 0.578148 | 15 | 131 |
| CANAL | 0 | 2 | 1 | 2 | 0.968153 | -2.1E-15 | 10 | 14 |
| Well | 5 | 0 | -3 | 4 | 0.524702 | -67.7028 | 26 | 26 |
| boundary point | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 |
| Dry wet Land | 1 | 3 | 1 | 2 | 0.946309 | -1.66259 | 16 | 29.000 02 |
| State_B | 1 | 4 | 1 | 4 | 0.75 | -90 | 8 | 7 |
| Toll | 0 | 2 | 1 | 1 | 0.867925 | -83.2088 | 7.3333 36 | 4.6666 49 |
| State_B | 1 | 4 | 1 | 2 | 0.705882 | 90 | 8 | 7 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Mine | 0 | 2 | 1 | 4 | 0.985915 | 78.88318 | 9 | 8.000019 |
| Pillars_S | 0 | 2 | 1 | 2 | 1 | 0 | 8 | 9 |
| Pole_S | 1 | 3 | 1 | 3 | 0.462069 | 75.24376 | 16 | 9 |
| State_B | 1 | 3 | 1 | 2 | 0.49635 | 70.88897 | 16 | 9.076925 |
| State_B | 0 | 0 | 0 | 3 | 0.530201 | 68.94066 | 15.85712 | 8.571443 |
| Post Office | 5 | 1 | -2 | 1 | 0.33871 | 86.22337 | 17 | 11 |
| Chatri | 4 | 4 | -1 | 4 | 0.285714 | 90 | 15 | 17 |
| Char | 0 | 2 | 1 | 2 | 0.4 | 73.62169 | 16.00005 | 11.39998 |
| Klin | 0 | 0 | 0 | 3 | 0.227692 | -50.6429 | 19 | 19.00011 |
| Char | 1 | 1 | 0 | 2 | 0.562963 | 61.00725 | 16.00002 | 10 |
| Circuit House | 3 | 3 | 0 | 2 | 0.468571 | 69.79112 | 16.00003 | 10.40001 |
| Circle | 0 | 0 | 0 | 2 | 0.202899 | 9.955771 | 21 | 22 |
| Char | 0 | 0 | 0 | 4 | 0.550633 | 67.76314 | 16.2627 | 10.10625 |
| Char | 2 | 2 | 0 | 2 | 0.516304 | -80.4615 | 16.00041 | 10 |
| Stream | 4 | 0 | -2 | 2 | 0.583333 | 65.65894 | 16.00014 | 11.24995 |
| Char | 0 | 2 | 1 | 4 | 0.451493 | 83.21506 | 21 | 12 |
| Church | 0 | 2 | 1 | 4 | 0.802469 | 88.94524 | 24.00002 | 7 |
| Circle | 2 | 2 | 0 | 2 | 0.48913 | 84.58799 | 21 | 12 |
| Police Station | 3 | 3 | 0 | 2 | 0.492754 | 86.89573 | 21.00004 | 13 |
| Char | 0 | 0 | 0 | 4 | 0.514925 | -88.8447 | 20.84209 | 13.57895 |
| Char | 0 | 0 | 0 | 3 | 0.516605 | 90 | 20.84208 | 13.57896 |
| Char | 1 | 3 | 1 | 2 | 0.5 | 87.13697 | 21 | 13.00004 |
| Char | 0 | 0 | 0 | 2 | 0.545455 | 89.20515 | 21.00006 | 13 |
| Stream | 0 | 0 | 0 | 2 | 0.543071 | -89.3612 | 21.00005 | 13 |
| Char | 0 | 2 | 1 | 2 | 0.459627 | 76.66654 | 22.00002 | 15.16668 |
| Stream | 3 | 1 | -1 | 2 | 0.567164 | 88.83869 | 21.00002 | 13 |
| Circle | 4 | 2 | -1 | 2 | 0.505848 | 87.29912 | 21 | 15.00003 |
| Char | 2 | 2 | 0 | 2 | 0.50578 | 59.64952 | 21 | 16 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Char | 0 | 2 | 1 | 3 | 0.479058 | 69.26998 | 23.000 01 | 18.142 87 |
| Circle | 3 | 3 | 0 | 2 | 0.455446 | 36.92403 | 21 | 17.600 01 |
| Char | 2 | 0 | -1 | 2 | 0.59697 | 88.87202 | 22.000 13 | 14 |
| Tank | 10 | 4 | -3 | 3 | 0.555305 | 88.88659 | 22 | 22.000 02 |
| Circuit House | 4 | 4 | 0 | 4 | 0.664179 | 87.22001 | 21 | 21 |
| Stream | 0 | 2 | 1 | 4 | 0.853333 | 86.18522 | 21.000 01 | 2.7857 12 |
| Boundary | 4 | 8 | 1 | 2 | 0.134975 | 0.004828 | 9 | 107 |
| Power Line Unsurveyed | 6 | 14 | 1 | 2 | 0.308362 | -0.08926 | 13 | 95.000 04 |
| POWERLI NE_S | 5 | 11 | 1 | 3 | 0.28582 | -0.15737 | 15 | 104 |

## 5.4 MAP UNDERSTANDING SUBSYSTEM (MUS)

The development process of automated topographic map understanding system has been planned as segmenting topographic map image, learning the invariant and common properties of a set of objects characterizing a specific meaning to object class and deciding the new object as a class by noting its common properties as those of the set of objects. The building blocks of proposed system have been shown in Figure 5.1.The steps and their dependencies for the development of an automatic understanding of (Indian Topographic) map have been shown through the flow graph in Figure 5.11. Two critical steps in designing the MU Handler in map understanding module are: First, to perform color-based layer segmentation along with effective computation of map symbol description, and second to evaluate obtained feature description using trained ANFIS.  For describing the pattern image, many representation schemes such as a point, linear and cell have been used. In the present study more flexible, the simple and general scheme having resemblance with human cognition for representation and description of the object has been adopted. In this scheme, the symbols have been represented using a color code and shape and structure parameters.

After segmentation of map objects from the background, the map layers are reconstructed/ the gaps in between the objects are filled. Once layers and map objects have been reconstructed, the shape of map objects has been represented and described in characteristic features for computer processing. Inference rules containing the legend Recognition Result have been extracted from initial legend data set created by LU subsystem. Integrating the information obtained from the LUS, an initial training data set has been created which has been used and modified further by MUS kernel. The MUS kernel learns Legend structure and generates shape feature descriptor which encodes the map object in terms of a shape or the feature parameters. This feature dataset has been evaluated on the training MUS kernel to obtain a map object description or semantic meaning.

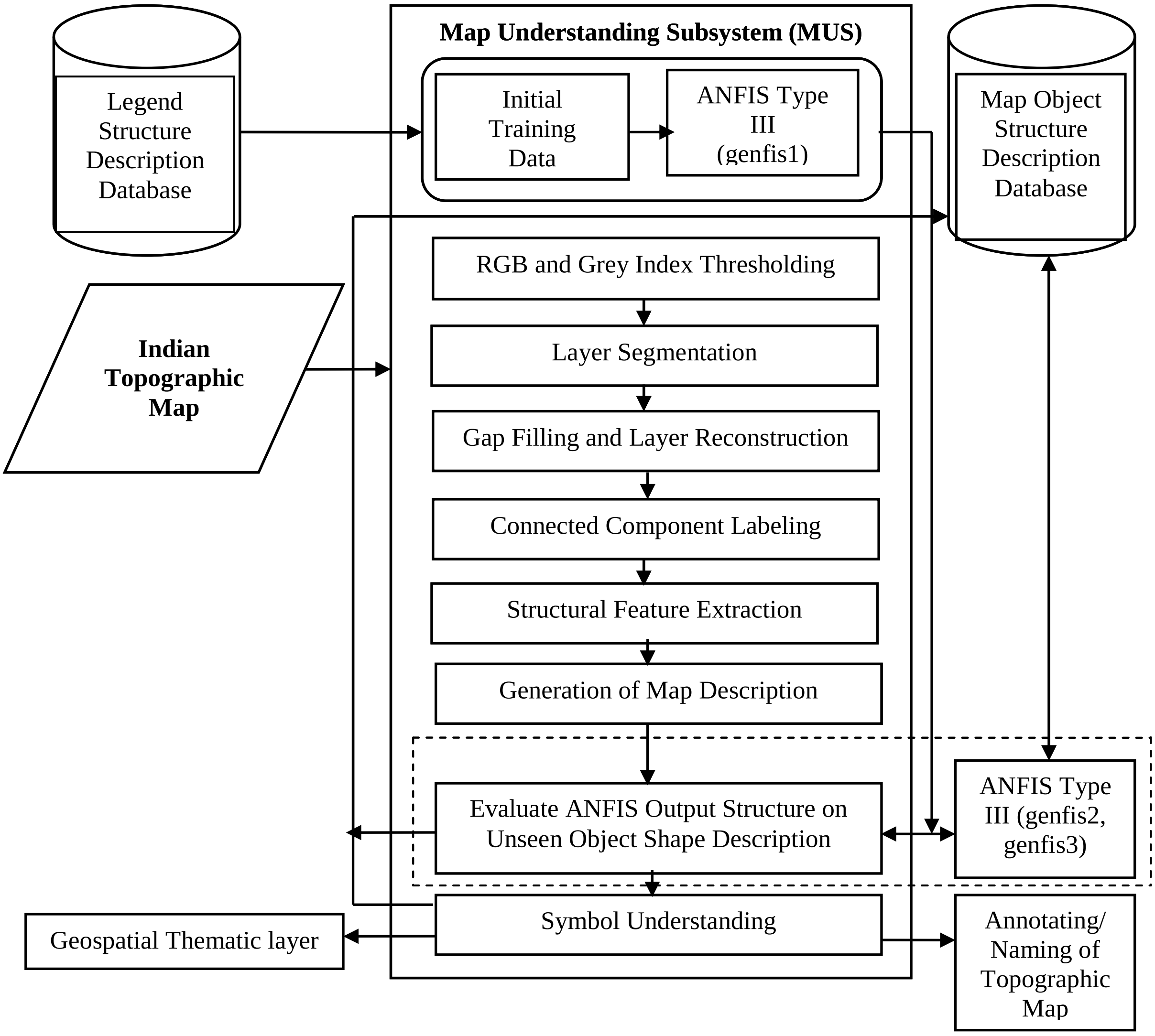



***Figure 5.11 Flow graph of Map Understanding subsystem (MUS)***

In the following sections, initial fuzzy inference system design, legend training dataset, and learning method are described. Next, description regarding object-oriented data model and object objects used for focusing on the symbol structure have been briefed. In the general sequence of operations in spatial understanding consists of ***MapGeoConverter*** to convert Georeferenced coordinates to pixel data and vice versa. Its conversion procedure has been detailed in section 5.4.3. The pre-processing module implementation, layer separation and feature extraction procedure, intelligent module implementation details have been provided in further subsections.

### 5.4.1 Initial FIS Design and Initial Legend Training Data Set

ANFIS a hybrid scheme, derives fuzzy IF–THEN rules with fitting membership functions derived from the training pairs, based on learning capability of the artificial neural network [139, 142]. With the development of Indian topographic map understanding system, ANFIS has been designed to incorporate the human way of thinking by using fuzzy sets. As ANFIS possesses the ability to interpret IF–THEN rules, ANFIS models have been implemented [161].A detailed description of ANFIS theory has been discussed more in reviews reported in [138, 139, 301]. In a preliminary analysis, a command genfis1 have been evaluated with different types of membership functions (including gbellmf, gaussmf, gauss2mf, psigmf, dsigmf, pimf, trapmf, and trimf) and different numbers of epochs to get the best training performance with a minimum squared error. It has been found that gbellmf has a high accuracy index and best suited in proposed application. For initial conditions of ANFIS training, a Sugeno-type FIS structure has been generated by genfis1. Ten generalized bell-shaped fuzzy membership functions (i.e. Gbellmf) have been used for the initial fuzzy inference system for generating representative rules.

TrainData = [lx ly]; It is an input-output pair: lx is shaping features and ly is expected output

```
NumMfs = 10;
MfType = 'gbellmf';
default_output_type = 'linear';
      InputFismat = genfis1(TrainData, NumMfs, MfType); //calling
function fis = genfis1(data, numMFs, inmftype, outmftype) //called
```

Thus, the resultant FIS has been stored in the variable Input Fismat. Initial legend structure database generated by LUS has been divided into 9 sets depending on the legend's color and shape peculiarity. Hence, total 9 FISs have been designed to generate representative rules for 9 categories of legends. The initial step of framing the rules has been done by grid partitioning subtractive clustering [140, 159, 344]. These methods have been used legend data set, having fewer numbers of input feature vectors and their membership functions. Hence, for forming the antecedents of the fuzzy rules, small input space have been partitioned into a number of fuzzy regions. The Grid partitioned fuzzy space in nine input models, with each input, is having ten membership functions as discussed. The number of rules generated depends on upon the input feature. For example, three rules have been generated for each node for the green legends dataset. The FIS for rectangular black legends, five rules have been generated. Also, for training dataset which contains the blue object, five rules have been generated by FIS using genfis1. The genfis1 or genfis2 has been used for initial FIS generation. The rules obtained from FIS have been optimized by using ANFIS methodology incorporated into MUS. The learning module has been described in the next section. The input,guassmf and output linear membership function have been employed. Later, for optimizing the learning procedure of the ANFIS models in each trial a hybrid learning algorithm has been employed. The algorithm has been developed based on least-squares method and backpropagation gradient descent method for training FIS membership function parameters [177] in emulating a training data set which has been obtained from LUS. Input data sets used in developing the Topographic Map Understanding models ANFIS techniques, have been reported in Table 5.5.

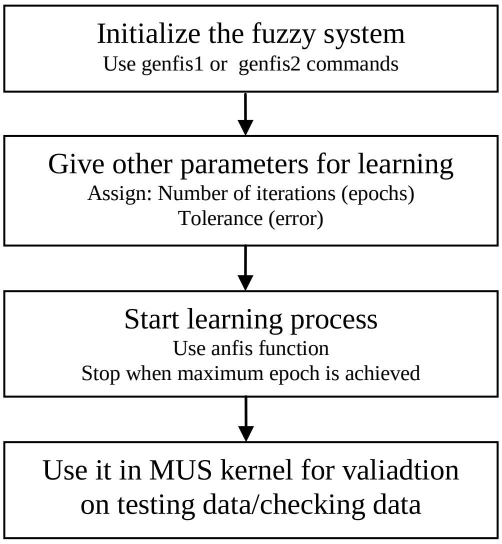



***Figure 5.12a. Initialization to optimization steps of the development of initial fuzzy model***

### 5.4.1.1 Learning module implementation

The training of system has been carried out by providing legend structure data and membership function created by FIS. After the training of system has been finished, the final membership functions and training error have been produced. The checking data have been used along with training data to increase possibilities to make a system understand map objects. Also, the system performance has been evaluated by providing input data set into the fuzzy system through the selection of a region of interest from topographic map. These data structure consists of a shape feature description of map objects present in that region and semantic meaning have not been present in that data. The output of ITMUS represents the semantic description code and provides a resultant understanding about the map object. The

The training procedure has been accomplished with the following steps: i. Propagates input features parameter values from the training data and determines the consequent parameters by learning algorithm while antecedent parameters remain fixed [247]. ii. The hybrid algorithm performs function forward pass by using the least square estimator and backward pass by gradient descent algorithm. It constructs input space-output space mapping based on both FIS's IF-THE rules and input-output data pairs [2]. It has been shown in Figure 5.12 b.

The parameters finding the shapes of MFs have been adjusted and modified during the learning procedure. For training the ANFIS independently 9 training dataset has been used after that, each training set has used cyclically. Every cycle through all the training examples termed as an epoch which comprises of a forward pass and a backward pass. The formation of consequent parameters and their adjustment have been done by the forward pass, while that of the backward pass alters the parameters of the activation functions [2]. Additionally, for the back propagation learning a gradient vector has been obtained recursively containing the derivative of an error measure with respect to the parameter.

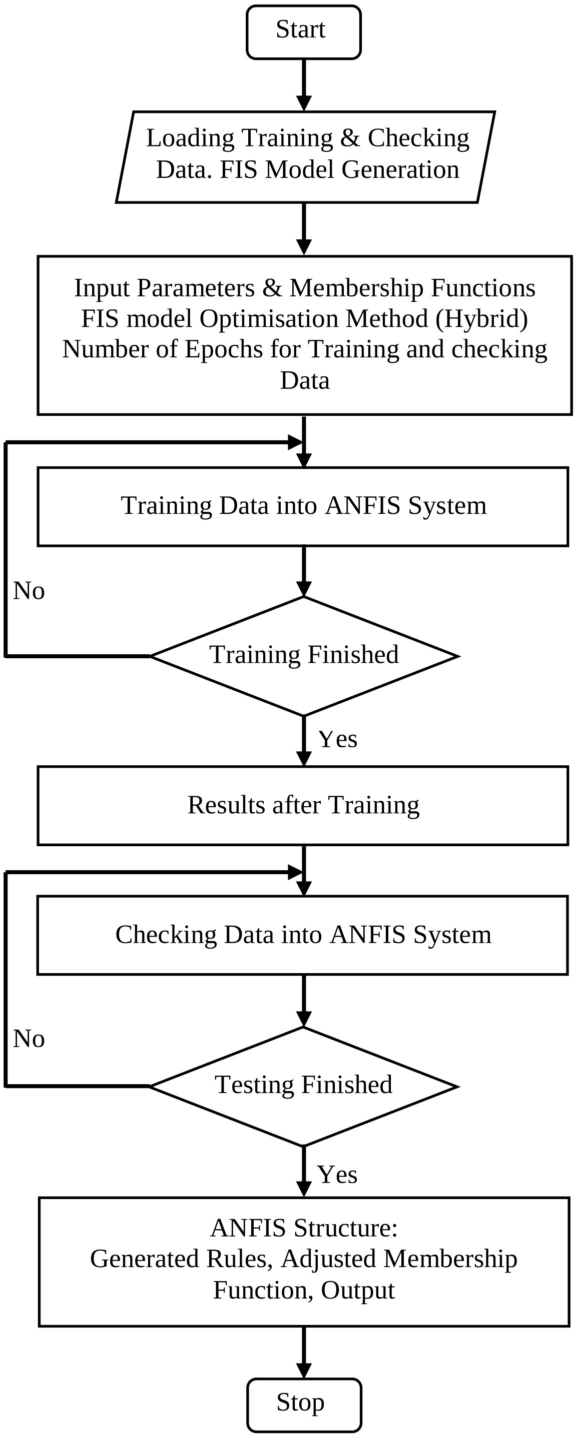



***Figure 5.12 b. Flow graph of training module***

Considering the output function of node $i$ in layer $l$

$$x_{l,i} = f_{l,i}(x_{l-1,1}, \dots, x_{l-1,N(l-1)}, \alpha, \beta, \gamma, \dots) \quad \text{Eq.(5.1)}$$

where $\alpha, \beta, \gamma, ..$ be the parameters of the node.

The sum of error can be defined has been defined as:

$$E_p = \sum_{k-1}^{N(L)} (d_k - x_{l,k})^2 \quad \text{Eq. (5.2)}$$

where $d_k$ be the desired output vector and $x_{l,k}$ both for the $k^{th}$ of the $p^{th}$ desired output vector.

The gradient vector has been calculated for passing the information on derivatives from the output layer till input layer i.e. moving in backward layer by layer.

α is a parameter of the $i^{th}$ node at layer $l$ and has been calculated as-

$$\frac{\partial E}{\partial \alpha} = \sum \frac{\partial E}{\partial \alpha} \quad \text{Eq. (5.3)}$$

Thus the generic parameter α is shown below:

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha} \quad \text{Eq. (5.4)}$$

where $\eta$ is the learning rate. So, parameter $\alpha$ is defined as

$$\alpha_{new} = \alpha_{old} - \frac{(-\eta)\partial E}{\partial \alpha} \quad \text{Eq. (5.5)}$$

For proposed hybrid learning algorithm, each epoch has to possess to pass, one forward pass and another one backward pass. Then Eq. (5.2) has been used for finding out the derivative of those error measures, which propagate from the output end towards the input end. The gradient vector has been determined for each training feature entry. At the end of the backward pass, the steepest descent method as given by Eq. (5.5) has been used for updating the input parameters [2].

***Table 5.5 Input data sets used in developing the Topographic Map Understanding models ANFIS Techniques***

| Input Dataset names (DSN) x ∈ $\{:, 5{:}end\ \forall X\}$ | y ∈ {Expected Output or target value} | ANFIS Output structure |
|---|---|---|
| bl3rec | {1,2,3,.........16} | blc3rec1.mat |
| bl3sq | {1,2,3,..........28} | bcl3sq1.mat |
| blu2l1 | {1,2,3,..........23} | blu2l1.mat |
| char | {1,2,3,..........66} | char.mat |
| grn | {1,2,3,............8} | grn_fis2.mat |
| r5l2 | {1,2,3,............9} | r5l2.mat |
| r5s1 | {1,2,3,..........23} | newr5s1_fis2.mat |
| sm2 | {1,2,3,............2} | sm2.mat |
| sm3 | {1,2,3,...........24} | sm3.mat |

The input-output pair [x,y] consists of x as a feature description and y as y ∈ {Expected Output}. The Semantic Meaning of Map objects and target value associated with map objects has been provided in the second column of Table 5.5 and elaborated in Table 5.6 to Table 5.14.

***Table 5.6 Input DSN: bl3rec- Black Line objects***

| Target value | Map object |
|---|---|
| 1 | Church |
| 2 | Light House |
| 3 | ML Cutting with Tunnel |
| 4 | L |
| 5 | Boundary_D |
| 6 | Boundary_S |
| 7 | Boundary_I |
| 8 | Mineral Line |
| 9 | Single Gauge |
| 10 | Double Gauge |
| 11 | Broad Gauge |
| 12 | POWERLINE_S |
| 13 | POWERLINE_U |
| 14 | Stream |
| 15 | Dam |
| 16 | Arrow |

***Table 5.7 Input DSN: bl3sq- Black Cell Object***

| Target value | Map object |
|---|---|
| 1 | Buoys |
| 2 | Broken ground |
| 3 | Tower |
| 4 | Temple |
| 5 | CHATRI |
| 6 | Church |
| 7 | Mosque |
| 8 | Idgah |
| 9 | Tomb |
| 10 | Lighthouse |
| 11 | Lightship |
| 12 | Anchorage |
| 13 | Surveyed Tree |
| 14 | Triangulated Height |
| 15 | Post Office |
| 16 | Telegraph Office |
| 17 | Rest House |
| 18 | Circuit House |
| 19 | Police Station |
| 20 | Klin |
| 21 | Circle |
| 22 | Island |

| | |
|---|---|
| 23 | Stream |
| 24 | Char |
| 25 | Tank |
| 26 | Antiquities |
| 27 | Rail under construction |
| 28 | Toll |

***Table 5.8 Input DSN: blu2l1-Blue objects***

| Target value | Map object |
|---|---|
| 1 | Shoal |
| 2 | Swamp |
| 3 | WELL_L |
| 4 | TUBE_WELL |
| 5 | Spring |
| 6 | Overhead tank |
| 7 | Police Station |
| 8 | Tourist Site |
| 9 | Veterinary Hospital |
| 10 | CANAL |
| 11 | Tank_P |
| 12 | Dam |
| 13 | 0 |
| 14 | 1 |
| 15 | 2 |
| 16 | 3 |
| 17 | 4 |
| 18 | 5 |
| 19 | 6 |
| 20 | 7 |
| 21 | 8 |
| 22 | 9 |

***Table 5.9 Input DSN: char-Black Characters, numbers, Alphanumeric characters Objects***

| Target value | Map object |
|---|---|
| 1 | A |
| 2 | B |
| 3 | C |
| 4 | D |
| 5 | E |
| 6 | F |
| 7 | G |
| 8 | H |
| 9 | I |
| 10 | J |
| 11 | K |
| 12 | L |
| 13 | M |
| 14 | N |

| | |
|---|---|
| 15 | O |
| 16 | P |
| 17 | Q |
| 18 | R |
| 19 | S |
| 20 | T |
| 21 | U |
| 22 | V |
| 23 | W |
| 24 | X |
| 25 | Y |
| 26 | Z |
| 27 | a |
| 28 | b |
| 29 | c |
| 30 | d |
| 31 | e |
| 32 | f |
| 33 | g |
| 34 | h |
| 35 | i |
| 36 | j |
| 37 | k |
| 38 | l |
| 39 | m |
| 40 | n |
| 41 | o |
| 42 | p |
| 43 | q |
| 44 | r |
| 45 | s |
| 46 | t |
| 47 | u |
| 48 | v |
| 49 | w |
| 50 | x |
| 51 | y |
| 52 | z |
| 53 | 0 |
| 54 | 1 |
| 55 | 2 |
| 56 | 3 |
| 57 | 4 |
| 58 | 5 |
| 59 | 6 |
| 60 | 7 |
| 61 | 8 |
| 62 | 9 |
| 63 | ( |
| 64 | ) |

| | |
|---|---|
| 65 | . |
| 66 | - |

***Table 5.10 Input DSN: grn- Green Objects***

| Target value | Map object |
|---|---|
| 1 | Scrub |
| 2 | Conifer |
| 3 | Palmyra |
| 4 | Bamboo |
| 5 | Palm |
| 6 | Grass |
| 7 | Plantain |
| 8 | TREES |

***Table 5.11 Input DSN: r5l2- Red Objects***

| Target value | Map object |
|---|---|
| 1 | Undefined |
| 2 | Fort |
| 3 | Hospital |
| 4 | Helipad |
| 5 | Aerodrome |
| 6 | Undefined |
| 7 | Undefined |
| 8 | Dam |
| 9 | CARTTRACK |

***Table 5.12 Input DSN: r5s1- Red Objects***

| Target value | Map object |
|---|---|
| 1 | Bridge |
| 2 | Deserted Village |
| 3 | Temp hut |
| 4 | Buoys |
| 5 | PO |
| 6 | RS |
| 7 | Dispensary |
| 8 | Dist Stone |
| 9 | Undefined |
| 10 | Arrow |
| 11 | Pack-track |
| 12 | Unmetalled Road |
| 13 | Cart track |
| 14 | 0 |
| 15 | 1 |
| 16 | 2 |
| 17 | 3 |
| 18 | 4 |
| 19 | 5 |
| 20 | 6 |
| 21 | 7 |

| | |
|---|---|
| 22 | 8 |
| 23 | 9 |

***Table 5.13 Input DSN: sm2- Black Objects***

| Target value | Map object |
|---|---|
| 1 | Graves |
| 2 | Embankments |
| 3 | Broken Ground |
| 4 | Pillars_U |
| 5 | Pillars_S |
| 6 | dot |
| 7 | Mine |
| 8 | Toll |
| 9 | State_B |
| 10 | Powerline_U |
| 11 | Island |
| 12 | Char |

***Table 5.14 sm3- Black Objects***

| Target value | Map object |
|---|---|
| 1 | Stream |
| 2 | Graves |
| 3 | Telegraph Office |
| 4 | Rail Line |
| 5 | Horz line |
| 6 | Power_Line_S |
| 7 | Antiquities |
| 8 | Broken Ground |
| 9 | Klin |
| 10 | Chatri |
| 11 | PO |
| 12 | Height Triangulated |
| 13 | Circle |
| 14 | Embankments |
| 15 | Lightship |
| 16 | Lighthouse |
| 17 | Island |
| 18 | Buoys |
| 19 | Mine |
| 20 | Pole_S |
| 21 | Char |
| 22 | State_B |
| 23 | Dry Tank |
| 24 | Pillar_S |

### 5.4.2 Object Oriented Data Model

The Geo-referenced topographic maps have been used in this study as the practical applications are much more. For the development of the understanding system, data organization has been instantiated properly in topographic maps. Also, the relationship has been recognized between the parts of maps describing the same territory on different sites. At the *conceptual* level, the system has been described by the class diagram shown in Figure 5.13. Indeed, each map in the repository has been tagged. The raster topographic map has been stored in TIFF format along with its georeference matrix. *Physical* and *logical*, structural hierarchies has been distinguished in the topological model. The topographical objects have been described using physical hierarchy by means of the physical entity, like point (dot), line (linear) or Cell (polygon). The Cell type of object has been represented by same physical entities in different series of maps, however, linear objects have been represented using isolines and depicted on the topographic map according to the ground truth. Spatial coordinates have been used to describe points, the centroid of a polygon.

Independent of the physical representation, the logical hierarchy has been expressing the semantics of geographical objects. As topographic maps have been stored using the conceptual data model, the entity *logical object* is a total simplification of eight distinct entities, namely, hydrography, hypsography, land cover, utilities, boundary, cultivation, construction and built-up area or urban area. Each of them is generalized further like a boundary has to be grouped in any one of the classes: Tahsil, state or international, which has been based on data organization model prepared by Cartography Environment of Survey of India. The automation in map analysis and resulting understanding also enables retrospective inspection of the map layers in the form of thematic layers for land use and terrain related knowledge in a simple to a complex level of understanding. The comparison of the obtained Geo-location based information and up-to-date information from GeoTiff metadata, which is created manually by Survey of India indicate a promising solution for manual map understanding process and the potential use of the system in large-scale land use planning and development.

### 5.4.3 Map Geo converter

*Georeferenced Coordinates To Pixel Data*

Maintaining Geo-location information along with topographical map symbol understanding has been necessary to get a spatial understanding about the map object. The following steps have been performed to achieve this objective:

1. Read a georeferenced topographic map into two-dimensional array and construct spatial referencing object, R.

   ```
   [I1, R] = geotiffread (full file (PathName, FileName));
   ```
2. Construction of spatial reference matrix.

For this, an affine spatial referencing matrix has been constructed using Refmx = makerefmat($X_{11}$, $Y_{11}$, $D_x$, $D_y$) with scalars $X_{11}$ and $Y_{11}$, where $D_x$ is the difference in x or longitude between pixels in successive columns, and $D_y$ is the difference in y or latitude between pixels in successive rows. It has been used for mapping the image or data grid as rows to map x and columns to map y. It uses information on the map location of the center of the first (1,1) pixel in the image.

```
Refmx = makerefmat(info.CornerCoords.Lon(1), info.CornerCoords.Lat(1),...
    ( info.CornerCoords.Lon(3)-info.CornerCoords.Lon(1))/m, ...
    (info.CornerCoords.Lat(1)-info.CornerCoords.Lat(3))/n);
la = (info.CornerCoords.Lat(1)-info.CornerCoords.Lat(3))/6;
lo = ( info.CornerCoords.Lon(3)-info.CornerCoords.Lon(1))/5;
LatLim = info.CornerCoords.Lat(1):-la:info.CornerCoords.Lat(3);
LonLim = info.CornerCoords.Lon(1):lo:info.CornerCoords.Lon(3);
```

3. Conversion of map coordinates to pixel coordinates

```
[r, c] = map2pix(R, pos(1),pos(2));
load(a);
row = [floor(r)-255+1 floor(r)];
col = [floor(c) floor(c)+255-1];
```

4. Conversion of pixel coordinates to latitude longitude coordinates

```
[lat1, lon1] = pix2latlon (Refmx, floor(row(1)),floor(col(1)))
[lat2, lon2] = pix2latlon (Refmx, floor(row(2)),floor(col(2)))
la = (lat1-lat2)/5;
lo = (lon2-lon1)/5;
LA = lat1:-la:lat2;
LON = lon1:lo:lon2;
```

5. Construction of reference matrix for pixel coordinates of map image or raster grid, which has been referenced and aligned with a geographic coordinate system.

```
Rfx = makerefmat(lon1, lat1,(lon2-lon1)/mm,(lat1-lat2)/nn);
```

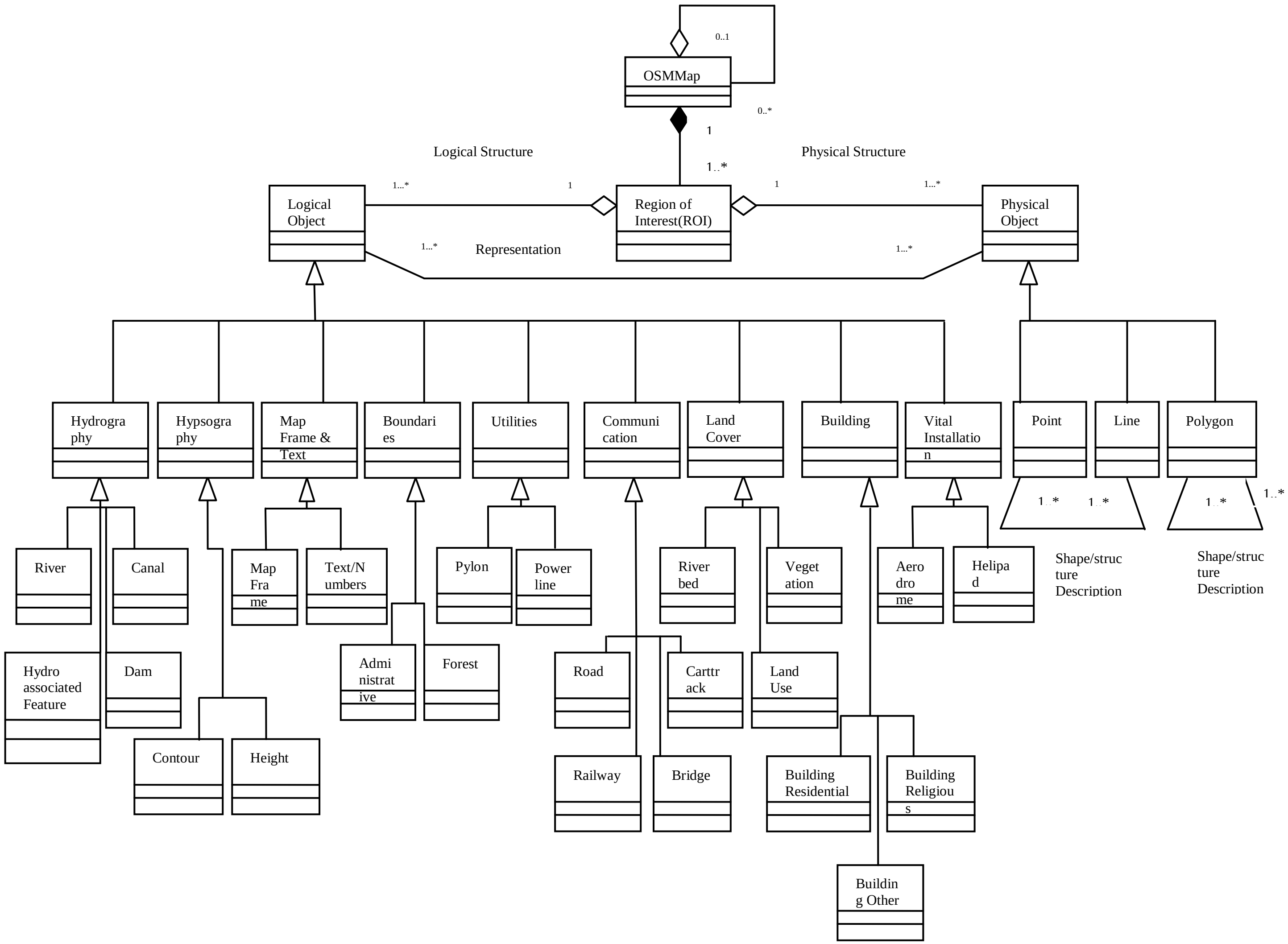



*Figure 5.13 Class diagram of ITMUS conceptual model in Unified Modelling Language (UML)*

### 5.4.4 Preprocessing Module

The three main algorithms have been used in the development of a preprocessing module to reduce noise. First, mask filtering has been employed with sequential 3x3 mask analysis and parallel 8-dilation and erosion; Second, detection and removal of very small points and holes based on a line gap filling algorithm; Thirdly, image enhancement by smoothing [2] has been carried out. The flow graph has been as shown in Figure5.18.

The thinning operation has been employed based on the algorithm reported by[127],has been further modified as per the need of the system. The objects having thickness 2wd+2 are stored, where 'wd' is a maximum thickness of the object. The object is thinned in a different amount of times as each object is having a different width. Further 8X8 mask is generated which is used to label each fully thinned pixel. But, the need to sort values makes it costly for implementation.

The preprocessing is prerequisite to the measurement of shape features and formation of a shape descriptor for further training of ITMUS. The basis is to get or to measure the feature set accurately which best fits or represents the symbol or object. Hence, if any overlapping or intersection is present, preprocessing step performs filtering and quantization to separate map layers. The discontinuity or gap is there, then the idea is to fill up or reconstruct the gap. The map objects are separated based on color coding as in Figure 5.6 (a). However, black objects, which are overlapped or intersected with the building has been removed from a region which left holes or gaps. The k nearest neighborhood algorithm has been used to determine the pixel that is to be connected with the current one to fill up the gaps. The distance between neighbors has been set which must be decreased to avoid such an over recovery. Its selection is crucial because in some places it is suitable, but in another situation this value may not be appropriate. So need some other parameter setting for optimal segmentation and reconstruction procedure.

#### 5.4.4.1 RGB and Gray index thresholding

Next, RGB to Grayscale conversion has been carried out by eliminating the hue and saturation information while retaining the luminance. Then image enhancement has been achieved by gray level slicing i.e. Intensity level slicing. All intensities below 240 have been preserved. Preserves other intensities image enhancement has been done by removing isolated pixels from the pattern image by the morphological operation. It applies operation for n=400 times and if the n='inf' then operation have been repeated until the image has no longer modification. In the current research work, the color topographic map segmentation has been carried out. Histogram thresholding has been used to find color values and to identify value ranges in a topographic map. The same approaches have been investigated by the researchers

[63, 233, 266]. The global and local maxima have been searching to find color classes. Next, based on gray level values, the cut level in RGB color space has been identified. Thus, each color layer possesses color values within cut level values in the color space cube. The approach has been combined with the approach developed in [74]. It has been used to define color code for objects of the different color layers. The processing of color code assignment of objects has been performed layerwise. The already recognized/isolated layers have been removed from topographic map [81]. This approach has been successfully incorporated in Digital Topographic map as all color values are clearly defined in these maps but needs to be tested on maps with higher variability in color values and false color.

#### 5.4.4.2 Layer segmentation

For the development of the module, color information, connected component labeling has been applied successively. The first step has been carried out by extracting red, green and blue color channels.

```
MaxGrayLevelR = max (redChannel (:));
%convert threshold into an actual number.
thresholdLevel = minGrayevelR + thrper*(maxgrayLevelR - minGrayLevelR);
BinaryImageR = redChannel > thresholdLevel;
```

The color code has been designed for separating the color layers in the topographic map. In the present study, GeoTiff raster topographic maps are used in which all colors are standardized and so as false colors are not included. The foreground color key has been, therefore, characterized by a vector in RGB space. For Indian topographic maps, this process results in three background color keys (white, green, and yellow) and twelve foreground color keys (black, blue variants (blue1 to blue3), green, red variants (red1 to red5), black. The developed color code book algorithm has been intended to sample pixel values without making a parametric assumption. Mixed pixels between foreground and background have been modeled by subtracting those pixels from the background inversion mask. Background colors have been recognized based on a gray index into Green, Yellow, White. Foreground Layers have been separated into six layers viz. Black, Brown, Yellow, Green, Blue and Red. Based on pixel thresholding, the interval has been assigned to actual numbers. Out of six foreground color layers, Red color and a blue color layer having variation have been further encoded based on red component and blue component respectively, in individual layers. Thus 12 foreground layers and 3 background layers have been obtained. The details of the color code estimation scheme have been shown in Figure 5.15. The color code has been generated by applying different architecture, which has been used in LUS. Their separation has been shown in Figure 5.14.

Background Layer Separation

```
for green background:
            if gray index>215 & gray index < 230
if green component > blue component
      color code = 12;
      else
            color code = 1;
      end
for Yellow background:
      elseif  gray index >230 & gray index < 250
color code = 13;
for Whitebackground
      elseif gray index >=250
      color code = 14;
Foreground Layer Separation
else
% Black foreground
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
if red component< 110 & green component< 110 & blue component< 110
color code = 0;
elseifred component == green component&green component == blue
component&red component<= 200
color code = 0;
% Yellow  %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
elseifred component> 200 &green component> 190  &( red component>= green
component) &green component> blue component&blue component < 100
color code = 11;
% Brown
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
elseifred component>green component&red component>blue component&red
component< 195 &red component >150
color code = 5;
% Red %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
elseifred component>green component&red component>blue component&red
component> 195
color code = 6;
% Green %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
elseifgreen component>blue component&green component>red component&blue
component< 200 &red component< 150
color code = 4;
% Blue %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
elseif (blue component>red component) & (blue component>green component)
color code = 1;
else
color code = 15;
end
end
        Out(ii,jj) = color code;
end
end
% figure, imshow(Out,[]);
Out1 = Out;

for i = 1:ro
for j = 1:co
if Out(i,j) == 6
red component = BW(i,j);
ifred component<253 &red component>=190
                Out1(i,j) = 6;
elseifred component<179 &red component>= 160
                Out1(i,j) = 7;
elseifred component<190 &red component>= 170
                Out1(i,j) = 9;
```

ITMUS
```
elseifred component <160 &red component>= 135%130
                Out1(i,j) = 8;
else
ifred component <135 &red component> 80% re<110 & re > 80
                    Out1(i,j) = 10;
end
end
end
end
end
% figure, imshow(Out1,[]);

Out2 = Out1;

for i = 1:ro
for j = 1:co
if Out(i,j) == 1
blue component = BW(i,j);
ifblue component >=200 &blue component< 250
                Out2(i,j) = 1;
elseifblue component >= 100 &blue component< 160
                Out2(i,j) = 2;
else
ifblue component >= 160 &blue component< 200
                    Out2(i,j) = 3;
end
end
end
end
end
% figure, imshow(Out2,[]);
```

***Table 5.15 Color code estimation scheme for layer separation***

| **Input** | **Foreground** | | | | | | | | | | | | **Background** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0-255** | **Black** | **Blue** | | | **Green** | **Red** | | | | | | **Yellow** | **Green** | **Yellow** | **White** |
| | | **B1** | **B2** | **B3** | | **Br** | **R1** | **R2** | **R3** | **R4** | **R5** | | | | |
| **Color Code Book** | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
| **Function** | `color_mx` | | | | | | | | | | | | | | |

For connected component analysis, the labelling of connected components in a binary map image has been carried out. This process assigns temporary labels to each foreground pixel as MATLAB stores matrix elements in memory, the process of scanning takes place along columns. As the scan meets the foreground pixel, a new label (1) has been assigned to it in the output. Next foreground pixel has also been assigned a temporary label of 1 in the output image if it has been encountered and its neighbor (any one) has already been received a label (1). When the scan is at row 2, column 4 pixel, the pixel has been assigned a new but temporary label of 2 as because there is no scanned pixel is present in neighborhoods. As Label 1 has been assigned to one of its scanned neighbors and label 2 assigned to another of the neighbors, the algorithm randomly picks one of the labels, and then records both referring to the same object. So, the labels 3 and 4 are similar and stored into the *equivalence table*. The matrix of label m has been generated at the end of this process. Based on *union find* algorithm, the equivalence class resolution has been performed. Equivalence class resolution is the process of determining which subsets of the temporary labels are actually referring to the same object.

#### 5.4.4.3 Gap filling and layer reconstruction

The map objects like polygon or cell type has been reconstructed based on a k nearest neighborhood (knn) algorithm. The three parameters have been considered to fill up the gaps between pixels such as a number of neighbors, distance between neighbors and the angle between neighbors. The angle between neighbors has been considered as infinity. As the gap filling algorithm has been applied to the individual binary layer, which has already been filtered and generated after color layer segmentation with minimal chances to interconnect different map objects due to gap filling. Hence the developed algorithm has been effective to reconstruct each color layer. As this has been done prior to feature extraction and description step, feature measurement of each map object can generate a representative feature vector for that map object. The block diagram of the overall gap filling algorithm has been depicted in Figure 5.15 and the results of gap filling and layer reconstruction have been shown in Figure 5.16, Figure 5.19 and Figure 5.20. Gray level histogram index analysis has been done for extracting the linear objects. The morphological operations of filtering, thinning have been applied to produce clean masks of one-pixel thick line. The line segments have been scanned to detect seed point and the whole line has been reconstructed using a k nearest neighbor algorithm. The method reported by other researchers [62, 268] has been inherited to resolve the gaps due to overlapping and/or intersecting with another kind of map objects. The layer reconstruction and surface plot algorithm have been illustrated for contour line and presented in Figure 5.17.

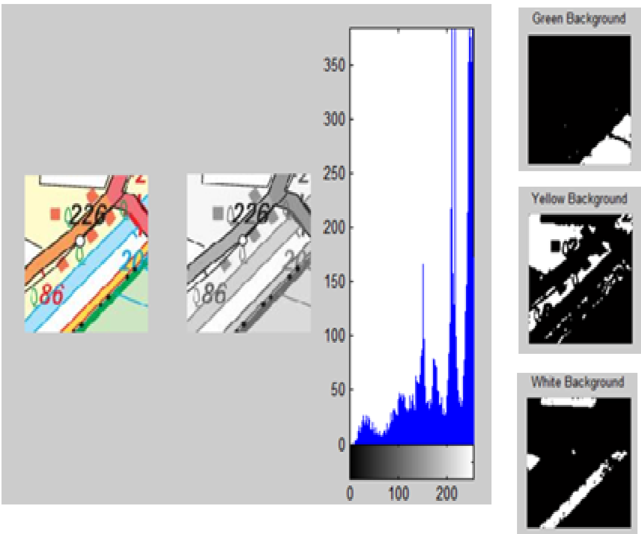



***Figure 5.14 Foreground and background separation based on color coding***

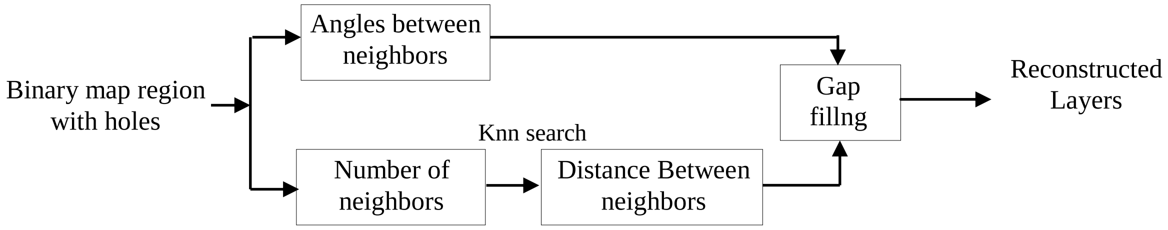



***Figure 5.15 Block diagram of algorithm followed to fill up gaps in map layers***


***Figure 5.16 Foreground layer separation and reconstruction***

The layer reconstruction is prerequisite to the measurement of shape features and formation of a shape descriptor for further training of ITMUS. The basis is to get or to measure the feature set which best fits or represents the symbol or object. Hence, if any discontinuity or gap is there, then the idea is to fill up or reconstruct the gap. In figure 5.19 a. Four building objects are appearing in map regions. These objects are separated based on color coding as in 5.19 d. However, black object which is overlapped or intersected with the building has been removed from a region which left holes or gaps. The k nearest neighborhood algorithm has been used to determine the pixel that is to be connected with the current one to fill up the gaps. The procedure has been depicted using a block diagram is given by Figure 5.15. It is based on distance, angle and number of neighbors. However, in Figure 5.19 e, two building objects are incorrectly connected. The distance between neighbors has been set to 3 which must be decreased to avoid such over recovery. Its selection is very critical because in some places it is suitable, but in another situation this may not be appropriate. So need investigation of some other parameters for optimal segmentation and reconstruction procedure.

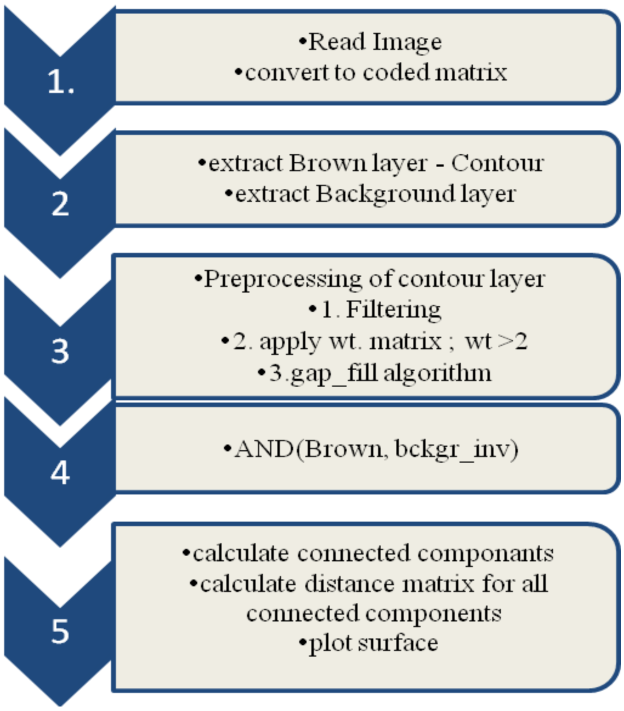



***Figure 5.17 Contour Layer reconstruction and surface plot algorithm***

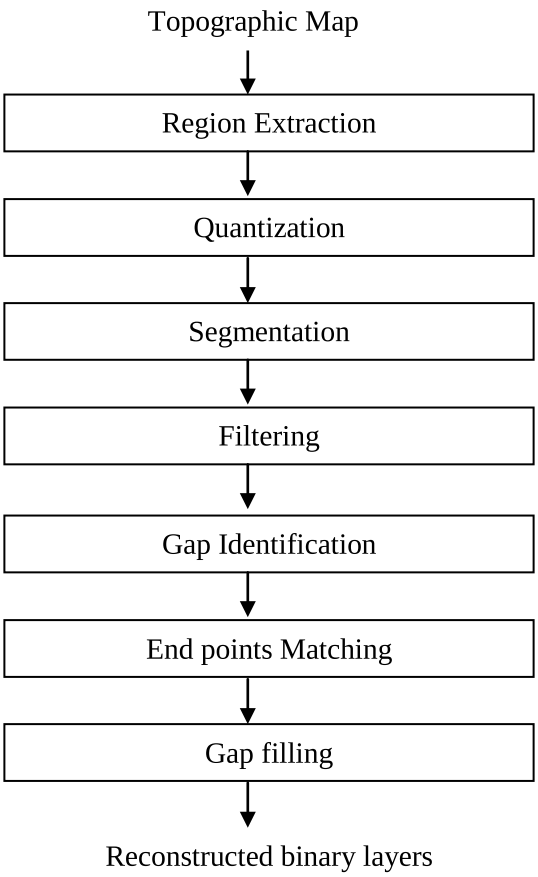



***Figure 5.18 Flow graph of map preprocessing algorithm***

Thus MUS has accomplished preprocessing and map layer segmentation before going for feature space measurement and pattern recognition. It avoids propagating errors or restricting uncertainty in defining feature descriptors which are a major task for pattern classification. The complete map preprocessing has been summarized in Figure 5.18.

### 5.4.5 Shape Feature Extraction

Feature space vectors which are object descriptors or patterns has used for analyzing the tasks associated with the map images. After segmentation and reconstruction, the map objects in each layer need to be described and represented in the computer for further processing. The features that represent the object have been used as descriptors. An automated extracting process for object boundaries from color images using color image segmentation and skeletonization has been reported in [284]. In existing approaches, the color image is segmented for getting an object or all the objects, after that its boundary have been modeled and based on generating points Delaunay triangulation has been constructed. Then, Voronoi vertices for all faces of the triangulation have been calculated. Different schemes like chain codes, Polygonal Approximation, Signatures, Convolution hull, Boundary Segments, the skeleton of a region boundary, have been used for representation. Descriptors as length or curvature; topological descriptors such as no. of connected elements and texture primitives (mean or standard deviation measures) and shape descriptors such as eccentricity, solidity etc. have been utilized. Morphology has been used in a mathematical context as a tool to extract image components which can either be boundaries, skeletons, or the convex hull. A segmented map object may contain multiple boundaries. So as shape parameters have been used to obtain a map object's description.

The proposed system has focused on 10 shape parameters and their measurements. Every map object detected, has undergone to intensive image processing and morphological operations. Mostly polygon shapes have been easily discriminated by their color and represented by their closed boundaries and connected pixels. Each polygon defines a shape, whose properties are very important for its semantic understanding. Other shape parameters have been derived from an object's connected component and their properties have been usually encoded in a more compact representation (i.e., map object feature vector).

#### 5.4.5.1 Generation of map objects descriptions

The coordinates of all pixels on a map have been calculated using *Map GeoConverter*, which binds the information for topographical objects inside each search area. Also, spatial and nonspatial properties of geographical objects have been extracted, such as their color and the coordinates of centroid points. Map objects on each layer have been automatically extracted from the search area. After that, the description of the each object has been created by means of the Feature Extractor. By applying algorithms for the derivation of geometrical properties, the map symbols *Descriptions* have been generated. The intermediate descriptors have been listed in Table 5.16. These descriptors encompass geometrical attributes like *contain* and *size_of*, a directional attribute like *coordinate_orientation*, a geometry attribute like *area*, and topological relationships like *shape_of*. Three descriptors independent of location have been described as *color*, *type*, and *subtype* [194].

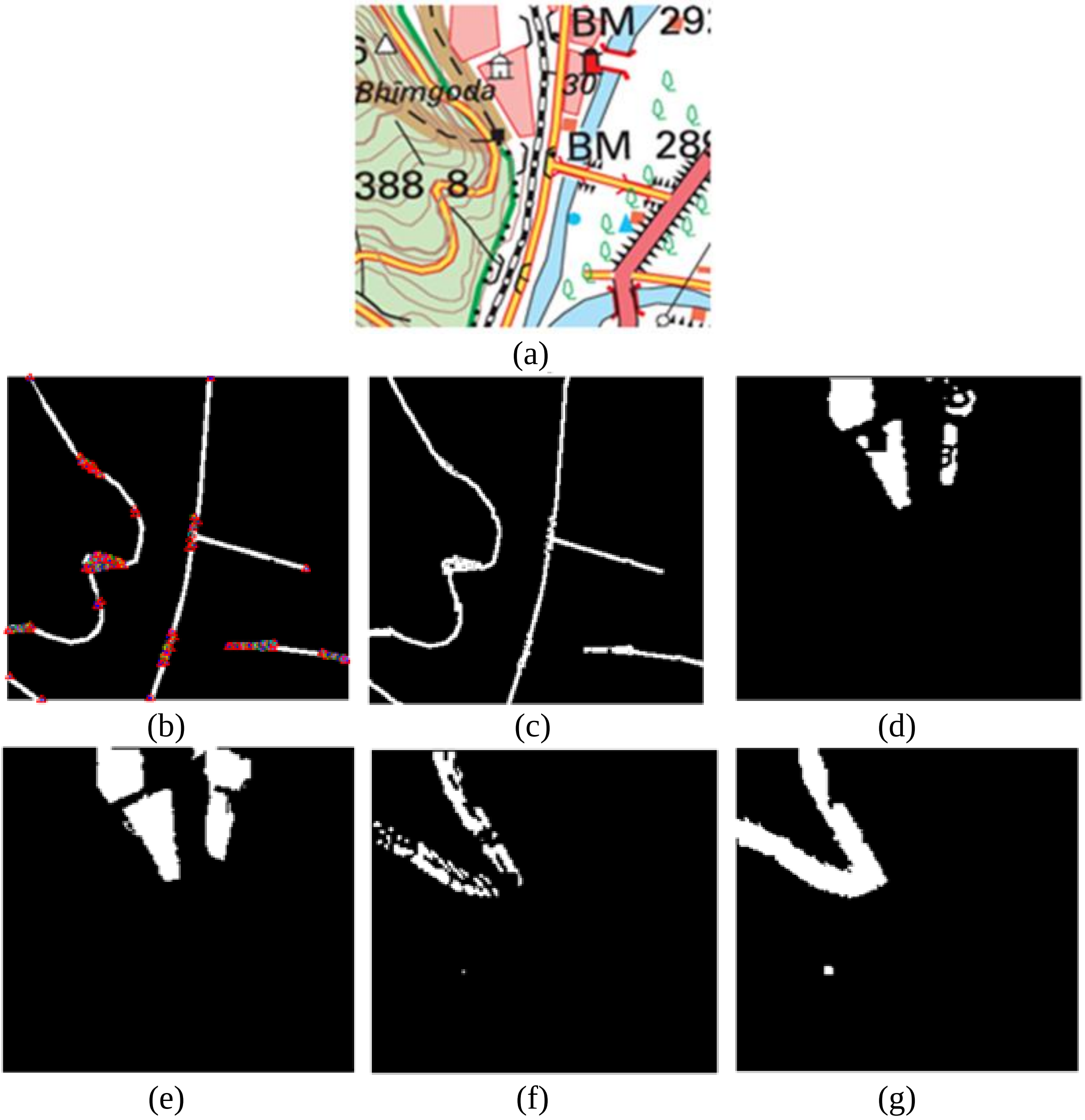



***Figure 5.19 Gap filling and layer reconstruction (a) Original topographic map region(b) Gaps in Road layer are identified, (c) Gaps in Road layer is filled up by the proposed algorithm, (d) Gaps and holes are appearing in building object, (e) building object is reconstructed by the proposed algorithm, (f) Boundary object is deconstructed due to black layer removal, (g)Boundary object is reconstructed by the proposed algorithm.***

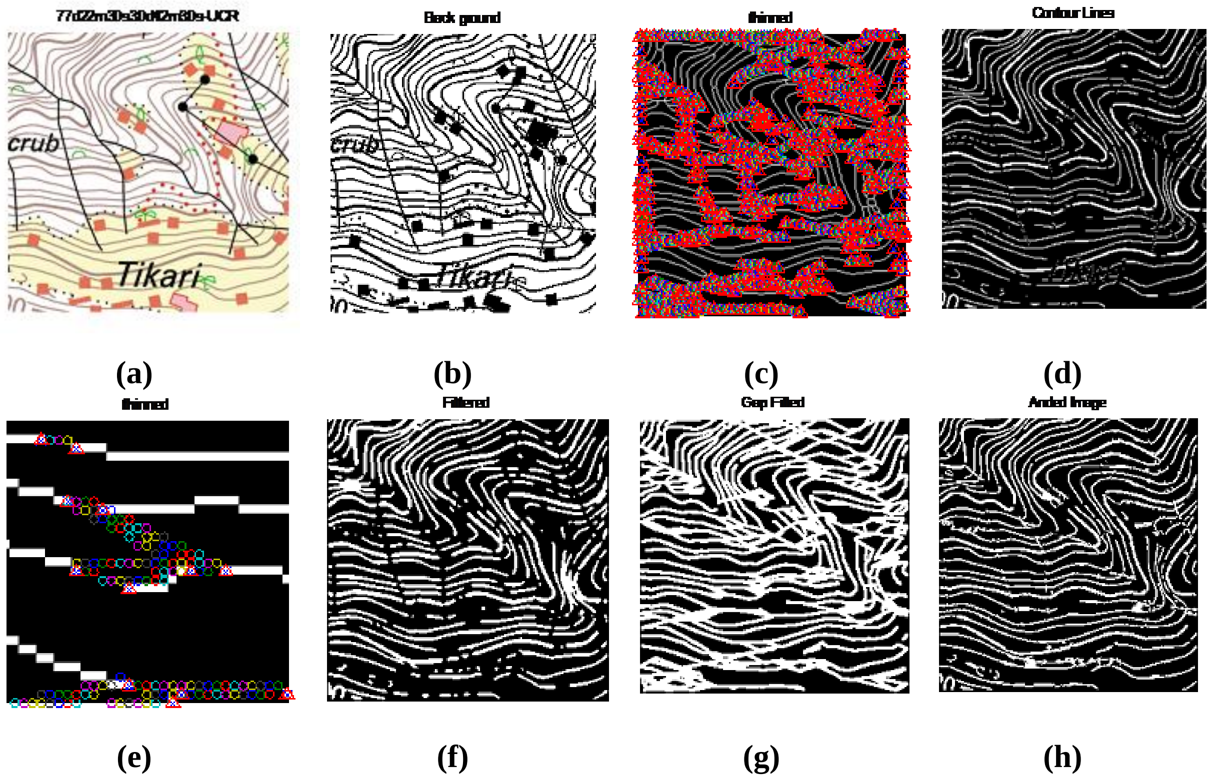



***Figure 5.20(a) Original topographic map portion, (b)Background is extracted,(c)Contour layer is extracted and thinned,(d) binary contour layer, (e) gaps are identified, (f) layer is filtered by average filter, (g) gaps are filled by the proposed algorithm,(h)binary ending on the original contour layer and binary mask to reconstruct contour layer.***

***Table 5.16 Intermediate Descriptors used for the Indian Topographic Legend/Map Understanding***

| Descriptor | Meaning | Domain | |
|---|---|---|---|
| | | Type | Values |
| *contain(X,Y)* | region *X* contains the geographical object *Y* | Boolean | {0,1} |
| *type_of(Y)* | Type of *Y* | Nominal | 9 nominal values |
| *subtype_of(Y)* | Specialization of the type of *Y* | Nominal | 211 nominal values that are specializations of the type_of domain |
| *color_of(Y)* | Color of *Y* | Nominal | {red, green, blue, brown, yellow, white, black} |
| *area_of(Y)* | Area of *Y* | Nominal | [0…MAX_AREA] |
| *solidity_of(Y)* | Solidity of *Y* | Nominal | [0…MAX_SOLIDITY] |
| *coordinate_orientation _of(Y)* | Coordinate orientation of *Y* | Nominal | {0…MAX_orientation } |
| *shape_of(Y)* | Shape of the linear object *Y* | Nominal | {Line, Triangle, Rectangle, Pentagon, Hexagon} |
| *Size_of(Y)* | Difference between major and minor axis of *Y* | Linear | [small, large] |

The descriptors *contain*, *type_of*, *subtype_of* and *color* have been computed always for each logical component in the cell of interest while other descriptors have been calculated if conditions reported in the third column of Table 5.16 have been fulfilled. The feature extraction process has been described in Figure 5.21.

**Procedure** feature extraction(region)
    **for**each object y in region do
      extract the feature descriptors
      extract all the admissible descriptor w.r.t. the logic sub_type of y
    **end for**each
**return** feature descriptor

***Figure 5.21Procedure of feature extraction***

The generation of few sample descriptors has been briefed. Unconstrained descriptor *color* has a nominal attribute, which depends on the nature of the object. So as the color of the hydrographic layer is blue and brown reflects hypsographic layer, otherwise it should be black. Being a property of the entity *logical_object*, *color* in the data model, hasn't required further computation.

For the nominal descriptor *shape* three different values have been considered, namely: linear, having value *Line*; cell having values *Triangle, Rectangle, Pentagon, Hexagon,* and dot or point. As the difference among $d_{wi}$'s exceeds a given threshold $\tau_{\text{extrema}}$, the value *extrema* have been associated with *the shape*. A check on a straight trend has been performed if the *extrema* condition does not satisfy. If the differences, $d_{wi}$ have been smaller than a threshold $\tau_{\text{straight}}$, which depends on the examined territory, then the value *straight* has been determined else the value generated based on extrema for the object. Here, cell means a polygon feature or map object constituting a symbolic entity possessing area.

The morphological binary operations have been applied to get the structural information of the map object. Thus, the number of branch points and end points have been calculated. Using convex hull and minimum bounding parallelogram technique eccentricity, centroid, solidity and area of object region have been measured. Next, the orientation of the object along the Y and X axis has been measured by a minimum bounding parallelogram. Further, object region properties such as extrema, Euler's number, major axis, minor axis have been measured. Based on extrema calculations, the tentative shape of objects has been determined. For example, the pentagonal shape was represented as the extreme points of the temple are connected while by connecting extreme points of the lighthouse, the hexagonal shape was created. All structural and geometrical properties calculated for the object have been stored. For example, object region consisting of im1 and im2. At this stage of processing objects, features have been extracted and measured. Color code has been assigned to each color layer and in each color, layer object has been described by feature vectors containing 10 features with respective values. The few topographic map symbols with geometric features and color features have been shown in Figure 5.22.

### 5.4.6 Map Understanding Subsystem Kernel

A hybrid system has been used in MUS kernel, which exhibits the ability of reasoning and learning a vague and imprecise topographic map symbol feature. It is an Intelligent Module which has been designed to implement ANFIS using subtractive clustering and FCM algorithm. It has a combination of two or more intelligent threads i.e. operational processes.

The fuzzy system lacks the ability to learn by itself to determine and identify the new or changing ground objects of the topographic map, while the ANN is ambiguous to develop human-like reasoning. If these two methods combined, then ANN shows better transparency while the fuzzy system improves the ability of learning. An effective model in the topographic map understanding has been built using the combination of the methods for quick and accurate prediction. The disadvantage of data acquisition has been removed by the development of LUS. Thus ITMUS by itself acquire an initial knowledge and scratch down some initial rules about the legend structure. In addition, the fuzzy set is a deterministic process for its membership parameters [166].With the implementation of ANFIS in MUS kernel, these problems have been sorted out. The MUS kernel used first-order Sugeno system for generating the if-then rules for mapping the input to the output. The basic architecture is shown in Figure 5.24, comprising three parts: ANFIS design; Learning and evaluation of ANFIS output structure of the unseen topographic map portion.

#### 5.4.6.1 FIS Design

The development of the MUS kernel has been started by generating an initial FIS**,** which may be further trained by the system. Fuzzy rules have been constructed from scratch by using a numerical feature description of map objects.

A well-identified family of rule induction techniques has been formed by Fuzzy clustering algorithm, which has been used to organize and categorize shape feature vector data. Also, the feature data has been partitioned into homogeneous groups. Data partitioning has been used for deriving the space partitioning and each cluster has been assigned to a rule. The process of rule generation and mapping of the dependency factors to the connection weight values have been used in the proposed system. Which has allows incorporating learning, handling of uncertainty and impreciseness in segmented map objects? The purpose of this proposed model has to provide a structure for learning algorithms as well as able to interpret in the form of fuzzy rules and to make capable of using prior rule-based spatial object knowledge.

The ANFIS has been used as the backbone of MUS kernel. The initial knowledge base was reported in already 5.4 along with the sample data set entries, which have been generated for legend image. As discussed earlier, based on the color and type of map symbols the initial training set entries have been divided into nine sets. The training data set: name, map, or object and their respective code details have been given in Table 5.6 to Table 5.14. For each training, set classifiers have been generated using genfi2 and genfis3. Further, each training data have been divided into 70% for training, 15% for testing and 15% for validation in order to avoid bias and early termination. The MUS kernel has been developed particularly as a parallel structure that learns from the training data set. The function genfis constructs a fuzzy inference system (FIS) using input feature vector and the meaning of map symbols.The membership function parameters of the fuzzy inference system have been adjusted based on back propagation algorithm along with the least square method [86, 243, 339]. This adjustment allows learning from the training data. The function genfis2 has been used to generate a Sugeno-type FIS structure using subtractive clustering in some ANFIS model design. It has been provided with separate sets of input feature vector and symbol's meaning code in output data as the input arguments.In determining the number of rules and antecedent membership functions, the sub-clustering function has been used by rule extraction method and then determine each rule's consequent equation based on linear least squares estimation. The genfis function returns an FIS structure with a set of fuzzy rules for covering the input feature space [166, 167, 196].

**5.4.6.1.1 genfis2**

It has been applied using, fismat = genfis2(X, Y, radii).

The parametric conditions for genfis2 have been as listed:

1. X: Each row contains the input shape feature values of the map objects
2. Y: Each row contains the output value i.e symbol description code.
3. Radii: Cluster center’s range of influence of data dimensions

The ranges of the influence of the all data space have been 0.5, as 9 has been data dimension (i.e. 'X' has eight columns and 'Y' has one column) and radii equals to 0.5. The radii have been applied to all data dimensions, i.e., with the given radius each cluster center has a spherical neighborhood of influence [103, 339]. The functions 'gaussmf' and 'linear' have been implemented as input membership function and output membership function respectively.

The cluster centers with subtractive clustering has been estimated using [C, S] = subclust (X, radii, xBounds, options) [103]. As in the matrix C, the function returns the cluster centers, each row shows the position of a cluster center. The range of influence of cluster centers has been given by Sigma values reflected in the vector S. The subtractive clustering method has been used to calculate the possibility that data point defines the cluster center based on the density of surrounding data points. The work reported in [103, 331] provides a subtractive clustering method which is an extension of the mountain clustering method. The sequential tasks performed by the algorithm are as follows:

1. Select the data points with the utmost possibility to be the first cluster center
2. Remove all data points in the close vicinity of the previous cluster center, to identify the next data cluster and its location
3. Repeat process, till all of the data, is within radii of a cluster center.

**5.4.6.1.2 genfis3**

The genfis3 has been used to design an FIS using fuzzy c-means (FCM) clustering by extracting a set of rules that predicts the symbol description based on the evaluation of the feature description [103]. Fuzzy Inference System structure using FCM clustering has been modeled by

fismat = genfis3($X_{in}$,$X_{out}$).

Sugeno-type FIS structure (fismat) has been developed by specifying input data as $X_{in}$ matrix and output data as $X_{out}$ matrix. Both the matrices have one column per FIS input and output respectively. 'Gaussmf' has been employed as an input membership function while 'linear' as output membership function. Separate sets of input and output data in the form input arguments have been needed by the functions. Hence, FCM function has been used for determining the number of rules and membership functions for antecedents and consequents in the rule extraction method. In following Table 5.17; the default inference method has been summarized. However, FCM design basis has been provided in the next section.

***Table 5.17: Default Inference methods***

| **Inference Method** | **Default** |
|---|---|
| AND | prod |
| OR | probor |
| Implication | prod |
| Aggregation | max |
| Defuzzification | wtaver |

**5.4.6.1.3Fuzzy C-means clustering**

The fuzzy c-means clustering method has been applied through the function FCM (data,cluster_n) to the data set. The input arguments are training data set; each row as a sample data point and the number of clusters. The output arguments consist of final cluster centers,in which each row shows the center coordinates, final fuzzy partition matrix and values of the objective function during iterations (obj_fcn) [103].

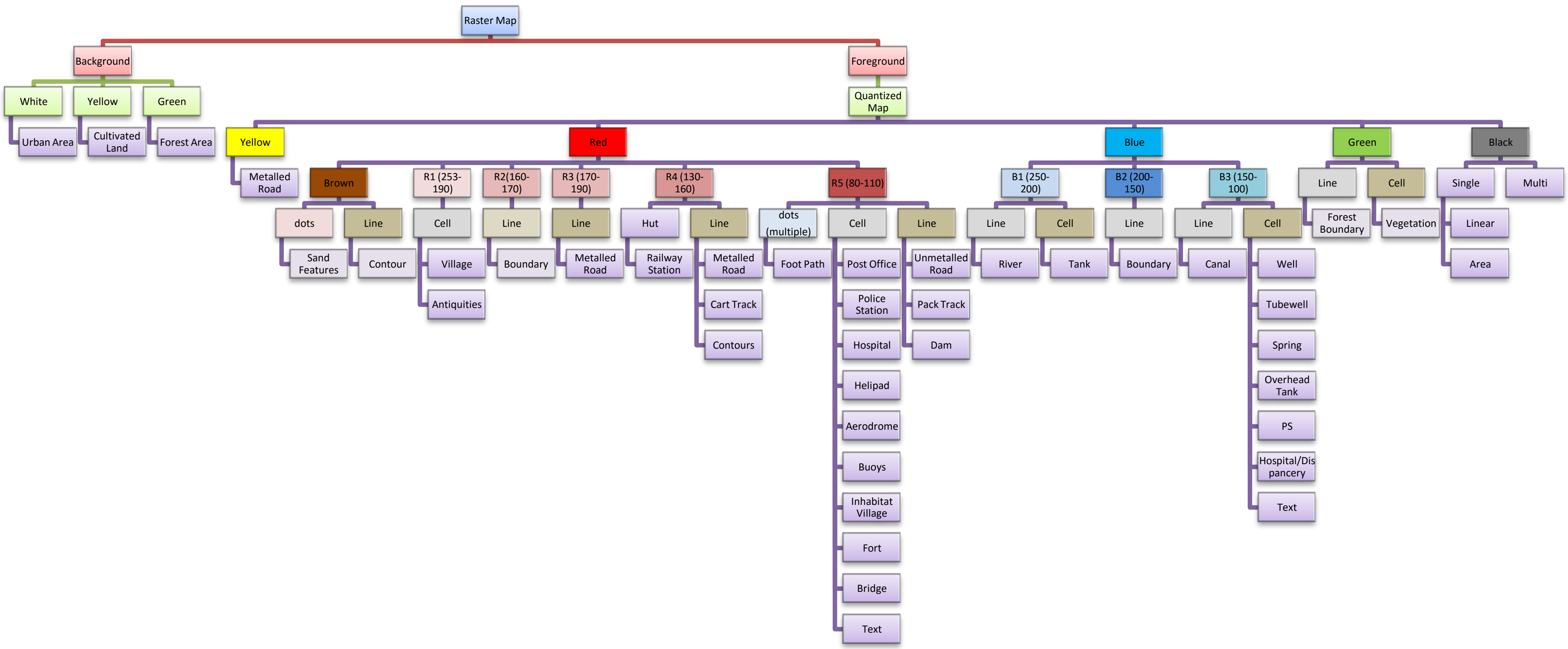



***Figure 5.22 Partial Spatial Object Ontology of few topographic map symbols***

Additional argument variables/options have been used by FCM for specifying clustering parameters which introduce topping criteria or set the iteration information display. Then, following options has been considered.

Options (1): Exponent for the partition matrix U. Default: 2.0.

Options (2): Maximum number of iterations. Default: 100.

Options (3): Minimum amount of improvement. Default: 1e-5.

Options (4): Information displayed during iteration. Default: 1

The clustering process stops, when 100 iterations have been completed. The FCM has been used to design 2 ANFIS model, one for understanding the rectangular black map objects and second for understanding toponym.

#### 5.4.6.2 MUS kernel design

An adaptive Neuro-fuzzy inference system (ANFIS) has been described in detail in [48, 141, 143]. In the present research work, multiple ANFIS models have been designed to implement MUS kernel. Each layer in the network represents the part of FIS namely: input fuzzification, rule inference and fire strength computation, and output defuzzification. FIS parameters have been encoded as weights in the neural network. Making use the representation theses parameters, have been further optimized using powerful, well-known neural net learning methods. Applications of neural networks in medical image analysis and medicine have been reported [237]. It has been implemented in satellite image analysis also [22, 218]. But rarely applied in map image understanding or map image interpretation. But, feed forward- the back propagation neural network has been used as functions of topographic legend recognition functions. In the preliminary study, feed forward-back-propagation neural network has been chosen due to its simplicity for testing the applicability of the machine learning technique on topographic legend image. Neural network processes the information as is done by the biological neural system. However, for obtaining the desired level of performance, many parameters need to be optimized [310]. Thus, the most effective features with the understanding model needs to be investigated. However, ANFIS has the ability to find out the effective features and development of the understanding model. The developed model is highly resembled with human thinking and understanding of topographic maps. Hence, in the development of MUS, ANFIS have been successfully implemented. It works on initial knowledge base which has been generated by the system itself and further successfully understands a variety of topographic map objects. A prerequisite is that the initial legend data set has to be divided into 9 training data sets. Each data set has been used as an input to initial FIS for rule generation. Then ANFIS has been designed in which these rules have been tuned or adjusted during training. The training data set details have been given in Table 5.19.

Trained ANFIS models have been used in individual map layers to understand map symbols in respective layers. Training set has been increased manually and the system has been trained till MUS generalize well on checking map regions. The training algorithm has been given in Section 5.4.1.1 using Figure 5.12 b. The MUS kernel predicts the semantic meaning of map symbol which has been further assigned and represented on a map region for better understanding. Due to object oriented hierarchical implementation (as given in Figure 5.13), MUS kernel gives intermediate as well as the abstract level of description of map symbols. The MUS kernel also generates map understanding summary and geolocation based dataset. MUS kernel interprets the map region in the form of thematic layers. The flow graph of MUS the MUS kernel design has been illustrated in Figure 5.23.For the development of the system, 9 ANFIS models have been designed based on object color and peculiarity in shape. These models have been using a Sugeno fuzzy inference system through a Neural Network approach. For Sugeno fuzzy inference system, it is easy to define output first which has been given by,

$$\hat{y} = \sum_{i=1}^{M} f_i \varphi_i\,(u) \qquad \text{Eq.(5.6)}$$

where,

$$\varphi_i(u) = \frac{\mu_i(u)}{\sum_{j=1}^{M} \mu_j(u)} \qquad \text{Eq. (5.7)}$$

It is used for normalization of the membership degrees of rule fulfillment by using the product t-norm, i.e.

$$\mu_i(u) = \prod_{j=1}^{p} \mu_{ij}(u_j) \qquad \text{Eq. (5.8)}$$

where, $u_j$is the j$^{th}$ component in feature vector, hence reflecting the value of the j$^{th}$ channel and $u_{ij}$ membership degree of $u_j$ with the fuzzy set describing the j$^{th}$ premise part of the i$^{th}$ rule. The $f_i$ is the consequent function of the M rules and have been defined by,

$$f_i = \omega_{i0} + \omega_{i1}u_1 + \omega_{i2}u_2 + \cdots + \omega_i u_p \qquad \text{Eq. (5.9)}$$

The ANFIS exhibits the network, corresponding to m-rule FIS, which has been made of 5 layers [138, 139, 140]. The ANFIS architecture has been seen from Figure 5.24, where nodes have similar functions as from the same layer. Each layer function has been described next. In MUS kernel, feature extraction module and multi-model ANFIS have been integrated. The 9 ANFIS models have been provided with 8 shape and structure features such as branches, end points etc. The trained ANFIS have been evaluated on topographic map region according to their color code. The topology of ANFIS model has been provided in Figure 5.25.

**Layer 1** Fuzzification of the input values using membership degrees

Every node *i* in this layer is an adaptive node with a node function

$$O_{1,i} = \mu_{A_i}(x), for\ i = 1, 2, .., n \qquad \text{Eq. (5.10)}$$

$O_{1,i} = \mu_{B_{i-2}}(y), for\ i = n+1, .., m$ Eq. (5.11)

Here, $x$ or $y$ is the input to the node $i$ and $A_i$ or $B_{i-2}$ is a quantifier associated with the node. In other words, $O_{1,i}$ is the membership grade of a fuzzy set $A$ ( $=A_1$, $..A_n$, $B_1,..,B_m$ ) and it denotes the degree to which, given input $x$ (or $y$) satisfies the quantifier $A$.

As provided in Section 3.4.5, the generalized bell function which is given in Eq. 3.8 has been incorporated as a membership function for $A$.

**Layer 2** Aggregation of membership degrees by using an appropriate t-norm applied in the premise parts. It is given in Eq. 4.4. It has been rewritten for n inputs.

Every node is a fixed node in this layer, the product of all the incoming signals is its output:

$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), i = 1, .., n$ Eq. (5.12)

The firing strength of a rule is represented by each node. In general, T-norm operators which perform fuzzy AND can be used as the node function.

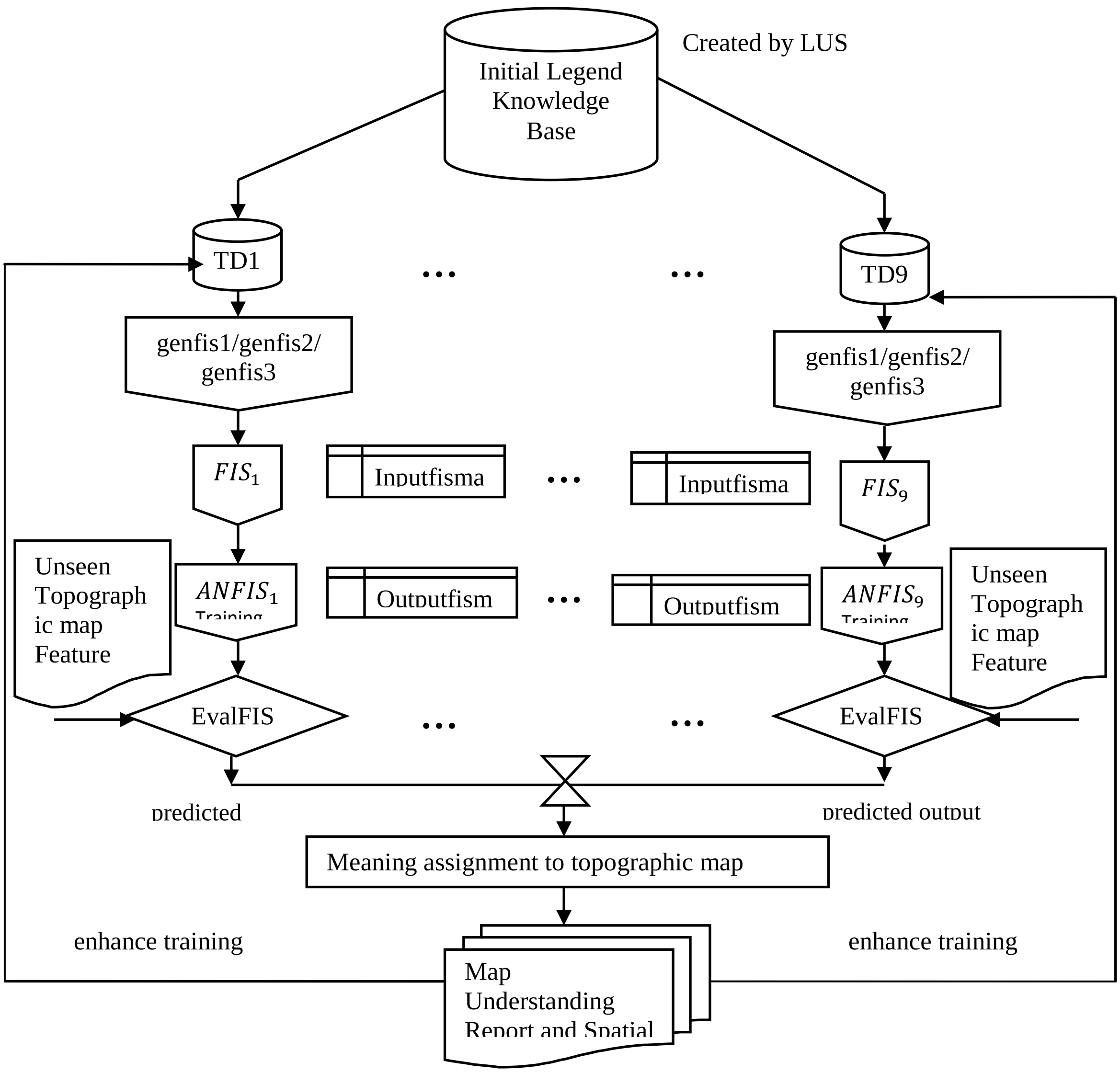



***Figure 5.23 Flow graph of MUS kernel***

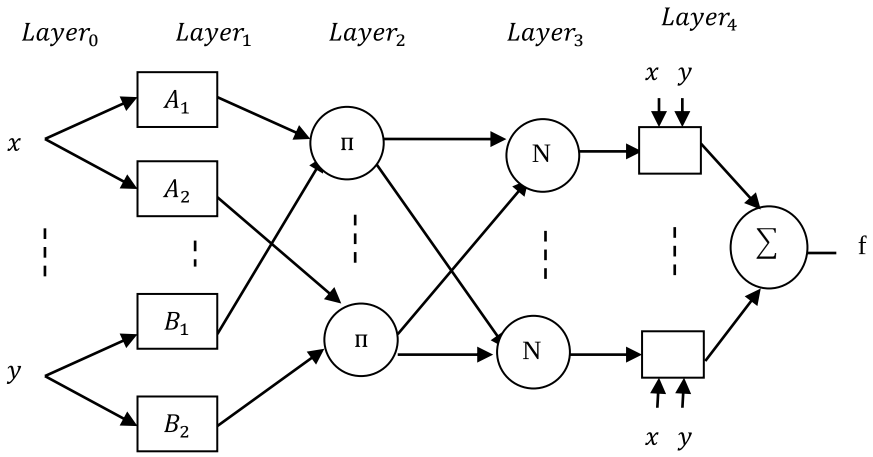



***Figure 5.24 Basic ANFIS model [139]***

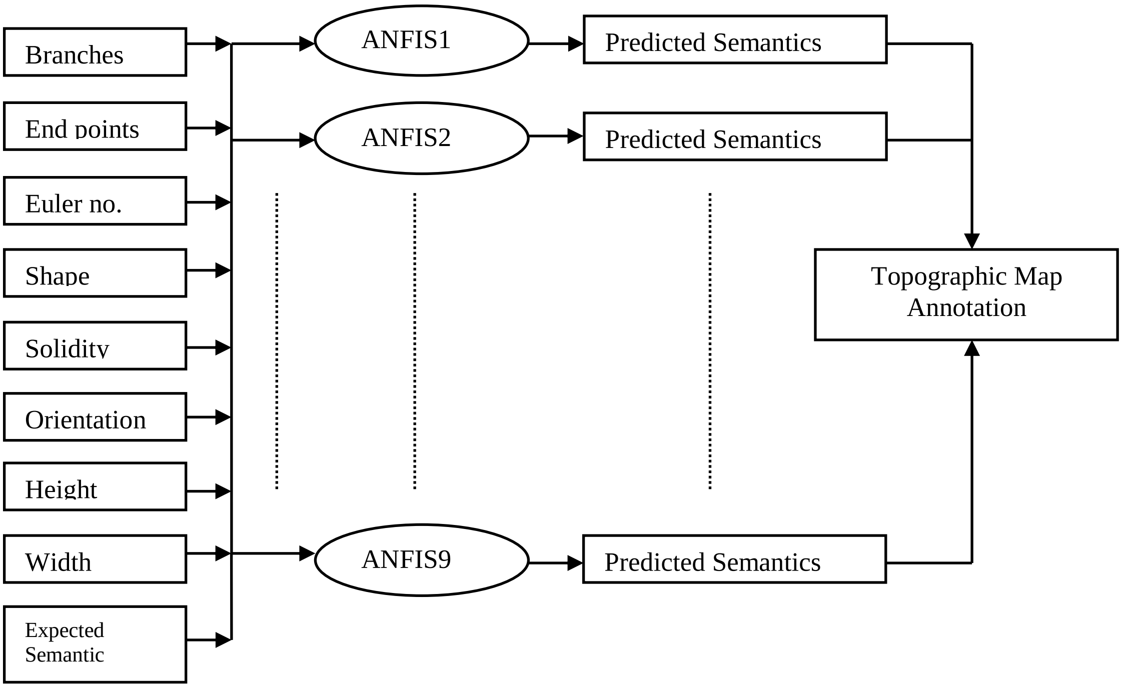



***Figure 5.25 Topology of ANFIS model to determine the symbol semantics in topographic map***

**Layer 3** Evaluation of the membership functions by normalization of aggregated membership degrees.

In this layer, each node is fixed and labeled N. The Eq. 4.5 has been rewritten. The ratio of the $i^{th}$ rule's firing strength to the sum of all rules' firing strengths calculated at $i^{th}$ node has been given as:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{\sum_1^n w_i}, i = 1, .., n. \qquad \text{Eq. (5.13)}$$

The outputs of this layer are called normalized firing strengths**.**

**Layer 4** Weighting of functions with linear or constant consequent functions

Each node is an adaptive node having a node function:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i), \quad \text{Eq. (5.14)}$$

where, $f_i$ is a normalized firing strength from layer 3 and {$p_i$, $q_i$, $r_i$} is the parameter set of this node. The parameters in layer 4 are referred as consequent parameters**.**

**Layer 5** Evaluation of output values by applying Eq. 5.1.

The single node in this layer is a fixed node, which computes the overall output as the summation of all incoming signals[139]

Overall output = $O_{5,1} = \sum_i \overline{w_i}\, f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$ Eq. (5.15)

Thus, the Sugeno fuzzy model has been constructed. This design leads to the possibility of generating only a sufficient rule, describing the relationship between input and output accurately enough.

**5.4.6.2.1 Learning Module Implementation**

As discussed previously, ANFIS maps input by using input membership functions and associated parameters. Also, maps through output membership functions and associated parameters to output. Input/output maps have been interpreted by using ANFIS. During the learning process, the parameters associated with the membership functions have been modified. Gradient vector has been used for computation of these parameters (or their adjustment/modification), which checks the modeling of input/output data by fuzzy inference system for the set of parameters. As the gradient vector (as given in Eq. 5.2) has been obtained, optimization takes place for adjusting the parameters to minimize the error which is defined as the sum of the squared difference between actual and desired outputs. The designed ANFIS use a combination of least squares estimation and back propagation for membership function parameter finding.

For mapping the feature space to decision space, membership functions have been used in the learning module. It attempts to search the rules, where data appear in the conclusions. The fuzzy rules of the network have been formulated using a rule mapping process. For learning the data set information, the Neuro-adaptive learning technique provides a method for fuzzy modeling. For adapting the parameters in the adaptive network, the hybrid algorithm has been employed. A hybrid algorithm is a combination of Steepest Descent and Least Squares Estimation (LSE), which comprises two passes; one is the forward pass and second is a backward pass [142]. For tuning consequent parameters, LSE has been used during the forward pass while for tuning the antecedent parameters Steepest Descent has been used during the backward pass. For each input, the experimental membership function has been set to the Gaussian type while the output membership function has been set to the linear type.It has been illustrated in Figure 5.6 a - Figure 5.6 b. The step-size adaptation parameters have been initialized to 0.1. For the 7 ANFIS model design, the potential of fuzzy subtractive clustering has been used to find the fuzzy rules for the corresponding ANFIS model. The radius of the clustering was changed until sufficient rules have been obtained. It has been provided in Section 4.4.2.6 by Eq. 4.1.

ANFIS system based on selected membership functions has been used for the construction of fuzzy if–then rules. The parameters have been iteratively changed in the pattern for minimizing the final error, and learning rule have used to specify the same.

The Eq. 3.10 which is given in Section 3.4 has been updated using a derivative of the overall error with respect to α, as:

$$\frac{\partial E}{\partial \alpha} = \sum_{p=1}^{P} \frac{\partial E_p}{\partial \alpha} \qquad \text{Eq. (5.16)}$$

Based on a hybrid learning rule algorithm, the ANFIS parameters have been trained. Using the least square method the parameters have been identified, as the functional signal advanced to layer 4 in the forward pass algorithm. This has been performed so as to minimize the measured error. While in the back propagation pass, gradient descent method has been used for updating the premise parameters. In input membership function, a Generalized Bell shaped function has been used while for output membership function ‘linear' has been chosen. There have been8 input variables (f1 to f8) with one output variable (Y).

Each epoch is having a forward pass as well as a backward pass in the learning model. An input vector has been presented in the forward pass and output has been recorded as a row in matrices x and y. All training data and the parameters modifiable node, i.e. parameters in RHS have been processed as specified. After identification of these parameters, the error for each pair has been calculated.

The propagation of the derivative of the error with respect to each node has been observed from output towards input. The Eq. 5.16 has been modified, rewritten as given below in order to obtain its derivative. The derivative of error measure has been calculated by,

$$\frac{\partial E_p}{\partial O_{i,p}^{L}} = -2(T_{i,p} - O_{i,p}^{L}) \qquad \text{Eq. (5.16)}$$

$$\frac{\partial E_p}{\partial O_{i,p}^{k}} = \sum_{m=1}^{k+1} \frac{\partial E_p}{\partial O_{m,p}^{k+1}} \frac{\partial O_{m,p}^{k+1}}{\partial O_{i,p}^{k}} \qquad \text{Eq. (5.17)}$$

The parameters are updated by the gradient method

$$\Delta\alpha = -\eta \frac{\partial \mathrm{E}}{\partial \alpha} \qquad \text{Eq. (5.18)}$$

After learning, the parameter of the membership shows good matching between input and output, leading to change the initial shape of the membership. The variables used for constructing the model, have been considered as effective variables if more changing observed for membership shape before and after the training. So as, the membership parameter and the Sugeno parameters have been used in the hybrid algorithm.

#### 5.4.6.2.2 Evaluation of ANFIS Model

The fuzzy inference calculations have been carried out to evaluate object's description set using trained ANFIS system using command given below,

Final Output= evalfis(input,fismat)

*The evalfis has been adopted with the following arguments:*

*input:*input values in Number or matrix form. If the input is a $M \times N$ matrix, where $N$ is the number of input variables, i.e. 8 features of the legends/map object, then evalfis considered the input row as an input vector and developed output in the form of $M \times L$ matrix having output vectors (rows) and output variables represented by $L$.

*fismat:* FIS structure to be evaluated.

*The range labels for evalfis are as follows:*

output: Output matrix of size $M \times L$, where input values represented by $M$(e.g. for blue layer 197), and output variables by $L$(which is 1) for the FIS.The details are given in Figure 5.26.

***Table 5.18 Training Data Set for Blue topographic features, bu2l1.xlsx***

| | Symbol Code | Symbol | Latitude | Longitude | Branches | End pts | Euler no | shape | Solidity | Orientation | Height | Width |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | shoal | 153 | 332 | 0 | 2 | 1 | 3 | 0.826923 | 79.30231 | 10 | 4.333335 |
| 2 | 4 | Swamp | 29.7116 | 76.2566 | 0 | 2 | 1 | 2 | 0.9704 | -82.6471 | 13.0001 | 10 |
| 3 | 9 | Veterinary Hospital | 29.5984 | 76.3597 | 5 | 0 | -3 | 4 | 0.5247 | -67.7028 | 26 | 26 |
| 4 | 7 | Police Station | 29.5984 | 76.3597 | 5 | 1 | -2 | 4 | 0.964 | 55.5357 | 19 | 16 |
| 5 | 10 | CANAL | 368 | 1414 | 1 | 3 | 1 | 3 | 0.443396 | 60.95947 | 13.00002 | 5.318153 |
| 6 | 11 | Tank_P | 349 | 181 | 0 | 2 | 1 | 2 | 1 | 0 | 1 | 29 |
| 7 | 3 | WELL_L | 11 | 401 | 0 | 1 | 1 | 2 | 0.991379 | 24.56526 | 11 | 11 |
| 8 | 4 | TUBE_WELL | 113 | 408 | 1 | 3 | 1 | 1 | 0.931818 | 89.73234 | 15 | 12 |
| 9 | 6 | Overhead tank | 355 | 1452 | 0 | 2 | 1 | 2 | 0.80303 | 51.71289 | 18 | 13 |
| 10 | 7 | Police Station | 353 | 1506 | 0 | 2 | 1 | 2 | 0.95858 | 52.14354 | 15.88237 | 8.117732 |
| 11 | 8 | Tourist Site | 342 | 1729 | 5 | 5 | 0 | 3 | 0.496487 | 40.31503 | 22.53339 | 24 |
| 12 | 9 | Veterinary Hospital | 342 | 1669 | 5 | 0 | -3 | 4 | 0.527211 | -77.34 | 26 | 25 |
| 13 | 5 | Spring | 173 | 491 | 0 | 2 | 1 | 3 | 0.782609 | 90 | 14 | 3 |
| 14 | 1 | shoal | 129 | 432 | 0 | 2 | 1 | 1 | 0.811321 | -81.2975 | 10.00004 | 4.285698 |
| 15 | 10 | CANAL | 364 | 1501 | 0 | 2 | 1 | 3 | 0.443299 | 62.51258 | 13.6191 | 4.571537 |
| 16 | 3 | WELL_L | 11 | 401 | 0 | 1 | 1 | 2 | 0.991379 | 24.56526 | 11 | 11 |
| . | . | | | | | | | | | | | |
| . | . | | | | | | | | | | | |
| . | . | | | | | | | | | | | |
| 197 | 18 | 5 | 29.5644 | 76.4174 | 1 | 3 | 1 | 4 | 0.8947 | -83.2621 | 17 | 11 |

Learn module enables the system to learn the relationship between input feature vector and output map symbol. By using this knowledge, the objects on the topographic map have been identified while by evaluating training models a new set of the feature description of objects have been recognized. Also, Learn module enables presentation of object categories and location or association of objects of a topographic map which has been recognized by ANFIS. The design of FIS and ANFIS, evaluation and parameters of the trained model with respect to the training data set of blue color map symbols, has been briefed in the subsequent paragraphs. The training data set of blue color map symbols named as 'bu2l1' as specified in Table 5.18.

```
inx = xlsread('G:\Implementation & Data\Implementation\Code for
GeoTiff\FinalSystem\Jan28\Legend Understanding Initial data
set\bu2l1.xlsx');
x = inx(:, 5:end);
y = inx(:,1);
TrainData = [x y];
NumMfs = 10;
MfType = 'gbellmf';
NumEpochs = 50;
StepSize = 0.1;
InputFismat = genfis2(x,y,0.5);
OutputFismat = anfis(TrainData, InputFismat, [NumEpochs nan
StepSize]);
save('blue_fis2.mat', 'OutputFismat');
yy = evalfis(x, OutputFismat);
```

**InputFismat** is 1X1 FIS Design which has been generated by genfis2 using 8 input vectors and 1 output vector as given in Figure 5.26 (a) and **OutputFismat** is <1X1> trained ANFIS Model which has been shown in Figure 5.26 (b).

### 5.4.6.2.3 Goodness of the classifier

Before evaluating the performance of ITMUS, it is necessary to evaluate the goodness of ANFIS used in ITMUS. It has been evaluated using $R^2$ value and based on some statistical measures. After which the efficient models have been selected and incorporated in MUS kernel. The Goodness of ANFIS has been defined as Correlation coefficient (R) which determines the relation between measured and model predicted symbols in training as well as testing stage. The correlation coefficient has been used as a measure, which shows the comparison between the trends predicted and actual [39, 139].It has been provided in section 3.5 by Eq. 3.15.

The number of intelligent threads ($N$) has been developed in an intelligent module with ANFIS models. It has been developed with topographic map object features as input and objects semantic/meaning ($U$) as output for topographic map data named as 53C7, 53F6, 53F7, 53F11, 53K1 of different territories in India (as given in Table 5.19). The individual model has been trained independently for a different number of training samples, whose details have been provided in Table 5.19. Out of N number of models, nine efficient models for nine categories, each includes a set of topographic map objects having a similar resemblance, were selected for modeling the five data sheets. Based on correlation coefficient ($R$) and *RMSE*, nine models have been selected. The output understanding about map object $U_t$ (t represents the number of objects to be recognized by that model), have been mapped with input feature i.e. $F_1$, $F_2$, ….., $F_8$ etc. and the previous learnt features i.e. $F_{1-p}, F_{2-p} \ldots\ldots, F_{8-p}$ etc. Based on the input data on the Indian topographic map, the models have been trained, tested and validated.

Name of FIS: 'sug81'<br>
type: sugeno<br>
andMethod: 'prod'<br>
orMethod: 'probor'<br>
impMethod: 'prod'<br>
aggMethod: 'max'<br>
defuzzMethod: 'wtaver'<br>
input: <1X8struct><br>
mf<1X5>type 'gaussmf'<br>
output: <1X1struct><br>
mf<1X5>type 'linear'<br>
rule: <1X5>

**(a)**

Name of FIS: 'sug81'<br>
type: sugeno<br>
andMethod: 'prod'<br>
orMethod: 'probor'<br>
impMethod: 'prod'<br>
aggMethod: 'max'<br>
defuzzMethod: 'wtaver'<br>
input: <1X8struct><br>
mf<1X5>type 'gaussmf'<br>
output: <1X1struct><br>
mf<1X5>type 'linear'<br>
rule: <1X5>

**(b)**

MFtype is 'gbellmf'<br>
NumEpochs 50<br>
NumMF 10<br>
stepsize 0.1000<br>
Traindata 197X9 [numrows X numcols]<br>
inx 197X12 Topographic map analysis data structure<br>
x is 197X8 input matrix<br>
y is 197X1 output matrix<br>
yy is 197X1 ANFIS evaluation result 'Measured o/p'

**(c)**

***Figure 5.26 (a) Initial FIS, (b) Trained ANFIS, (c) Trained ANFIS model evaluation and parameters***

Using above specified, the ability of each model has been studied properly. An absolute error has been reported by using dimensional criteria as root mean square error method. The performance of two models having same data has been compared by the criterion and used for their development. The degree of correlation between actual and measured values has been represented by a correlation coefficient. The value of Coefficient of efficiency varies based on the initial variance of observed data [36]. These performance indices have been discussed in Section 3.5 and have been used for evaluating the quantitative evaluation of ANFIS models during the testing stage which has been reported in Table 5.20. For a better appreciation of the model, the performance indicators have been used for checking the predictive effectiveness of ANFIS model. The predictive capability of the model has been judged by using Correlation Coefficient [36], Mean Square Error (MSE), Normalized Mean Square Error (NMSE),Root Mean Square Error (RMSE), and Coefficient of Efficiency ($R^2$) [26, 35]have been used as performance indicators and the performance of the different models has been discussed in section 3.5 and reported in Table 5.20. These performance indicators have been calculated using Eq. 3.11, Eq. 3.15 and Eq. 3.16 respectively. Efficient five models (for topographic map objects which are black in color) have been compared, showing better prediction on a topographic object which is black and tentatively rectangular in shape by ANFIS-Bl3rec4model hence used in MUS kernel.

***Table 5.19 Model development of various MUS models for topographic map symbols understanding***

| Model with training samples | Output | Input |
|---|---|---|
| TD1-MUS-1....1n {177} | $U_{t1}$ | $F_1, F_2 \ldots\ldots, F_8$ |
| TD2- MUS -2....2n {400} | $U_{t2}$ | $F_1, F_2 \ldots\ldots, F_8$ |
| TD3- MUS -3....3n {217} | $U_{t3}$ | $F_1, F_2 \ldots\ldots, F_8$ |
| TD4- MUS-4....4n {336} | $U_{t4}$ | $F_1, F_2 \ldots\ldots, F_8$ |
| TD5- MUS -5....5n {1026} | $U_{t5}$ | $F_1, F_2 \ldots\ldots, F_8$ |
| TD6- MUS -6....6n {206} | $U_{t6}$ | $F_1, F_2 \ldots\ldots, F_8$ |
| TD7- MUS -7....7n {1418} | $U_{t7}$ | $F_1, F_2 \ldots\ldots, F_8$ |
| TD8- MUS -8....8n {341} | $U_{t8}$ | $F_1, F_2 \ldots\ldots, F_8$ |
| TD9- MUS -9....9n {488} | $U_{t9}$ | $F_1, F_2 \ldots\ldots, F_8$ |

***Table 5.20 Best MUS kernel (implemented by ANFIS classifier) for Black rectangular shaped topographic map objects***

| Best Model | RMSE | $R$ | $R^2$ |
|---|---|---|---|
| TD1--Bl3rec1 | 0.52322 | 0.912 | 0.856 |
| TD1--Bl3rec2 | 0.50245 | 0.925 | 0.861 |
| TD1--Bl3rec3 | 0.49348 | 0.929 | 0.862 |
| **TD1-Bl3rec4** | **0.49032** | **0.934** | **0.864** |
| TD1--Bl3rec5 | 0.49428 | 0.934 | 0.862 |

Along with the statistical measurements, the model reported by Haykin [121] has been used for checking the model's ability to predict the output correctly when the input data are slightly different than the data used in building the model. It has been illustrated in Table 5.21 and Table 5.22 a. Also, the effect of the size of training data for predicting the output has been checked. It has been summarized in Table 5.22 b for this reason; the ITMUS has been evaluated using a random selection of a region of interest and their measurements as unseen data.

If predicted values are incorrect then that input feature set has been added to training dataset which helps to increase training dataset. As the training set size effects on classification performance, the broad training set shows better classification performance.

From Table 5.21, it can be seen that classification accuracy increases as increasing in the training set size. An understanding accuracy of 88.23% has been achieved when 4609 training samples each of containing 9 input parameters have been used. This reflects that the system still has the capacity to improve if additional training samples become available.

***Table 5.21 Overall accuracy as function of the training set on the MUS***

| Training set size | Test set size | Accuracy (%) |
|---|---|---|
| 350 | 270 | 54.89 |
| 780 | 270 | 66.24 |
| 1230 | 270 | 79.50 |
| 2300 | 270 | 85.32 |
| 4,609 | 270 | 88.23 |

Making a large and a representative training set available has been time-consuming and not feasible. So, the assumption of the availability of a compressive training set at the initial stage is impractical. For overcoming the problem, the incremental learning in a classifier has been incorporated by the researchers [308, 333].

Also, in building the ANFIS architecture the type and number of membership functions have been critically checked. A variety of different training data sets and checking data have been used to examine the effect of type and number of membership functions. The selection of final ANFIS model has been made based on statistical measures before incorporating it in MUS kernel. The models have been evaluated based on their performance measures (RMSE and MAE) in training and checking data sets. The statistical measures RMSE and MAE have been explained in section 3.5 and have been expressed by Eq. 3.11 and 3.14. The models have been selected based on their performance variation against the evaluation criteria in terms of data sets, the number of membership functions, type of membership function and lower RMSE values. The selected ANFIS and their structural information are reported in Table 5.22 a. The result in the Table5.22 demonstrates that MUS kernel obtains acceptable ANFIS model performance to interpret map objects and also seen that ANFIS have been successfully applied to topographic map content.

As discussed in section 3.5, the performances of the developed models have been evaluated using various standard statistical performance evaluation criteria. The statistical measures, namely, the root mean square error (RMSE), % RMSE and accuracy have been being computed using Eq. 3.11, Eq. 3.12 and Eq. 3.13 respectively. The statistical measurements have been given in Table 5.22 b. The root mean square error (RMSE) for train data set is 0.83, % of RMSE is 30.00, and for check data set is 1.55, %of RMSE is 47.65. The execution time, usually not exceed a few tens of seconds on Intel(r) Core i7-4510U CPU of

2.00GHz, 2001 MHz,x64based PC, 2 core(s) and 4 logical processors. The total time depends on the complexity of the region of interest, the number of color layers in the region of interest, the number of objects, and the set of the used operations. The average time for understanding the 256X256 size region of interest is 1-2 minutes.

***Table 5.22 (a). Multimodel ANFIS structure information employed in MU kernel***

| ANFIS parameter | ANFIS1 | ANFIS2 | ANFIS3 | ANFIS4 | ANFIS5 | ANFIS6 | ANFIS7 | ANFIS8 | ANFIS9 |
|---|---|---|---|---|---|---|---|---|---|
| Number of inputs | 9 | | | | | | | | |
| Membership function type | Gaussian | Gaussian | Gaussian | Generalised bell-shaped | Gaussian | Generalized bell- shaped | Generalized bell- shaped | Gaussian | Gaussian |
| Number of membership functions | 10 | | | | | | | | |
| Training Data set | 130 | 130 | 110 | 130 | 115 | 130 | 125 | 130 | 110 |
| Checking Data set | 108 | 105 | 123 | 103 | 118 | 105 | 110 | 103 | 115 |
| Epoch number | 50 | | | | | | | | |
| RMSE | 0.4903 | 0.6726 | 0.4768 | 0.0641 | 1.1206 | 0.7143 | 0.5434 | 0.4260 | 0.5539 |
| MAE | 0.239 | 0.3244 | 0.2456 | 0.0234 | 0.5512 | 0.33 | 0.2589 | 0.2137 | 0.2896 |

***Table 5.22( b). Multi Model ANFIS performance estimation using statistical measures***

| | **Multi-model ANFIS Performance (Average of 9 models)** | | |
|---|---|---|---|
| **Data set** | **RMSE** | **%RMSE** | **Accuracy** |
| Train data set | 0.83 | 30.00 | 93.00 |
| Checking data set | 1.55 | 47.65 | 90.36 |

### 5.4.7 Map Representation Module Implementation

The utility of the map interpretation system has depended on the production of output products that effectively convey the interpreted information to end user. In ITMUS, the Indian topographic map image has been represented hierarchically corresponding to increasingly higher levels of abstraction oriented towards capturing its "direct/semantic meaning" of the objects that are represented in map image and measured numerically at the lowest level. Interpreted map (i-map) representation deals with presenting the annotated Indian topographic map inside the search window which has been provided to its end user. Representation module has been implemented in such a way that it provides insight to the user to get the i-map and enables to extract the color and feature-based layer information. Also, it provides accessibility towards the semantic geolocation based map layers for the user. Representation module enables the system to display geolocation and intermediate information about each map object. It allows exploring the map objects under a specific category. The random selection has been made and processed by ITMUS. The resultant i-map has been shown in Figure 5.27.

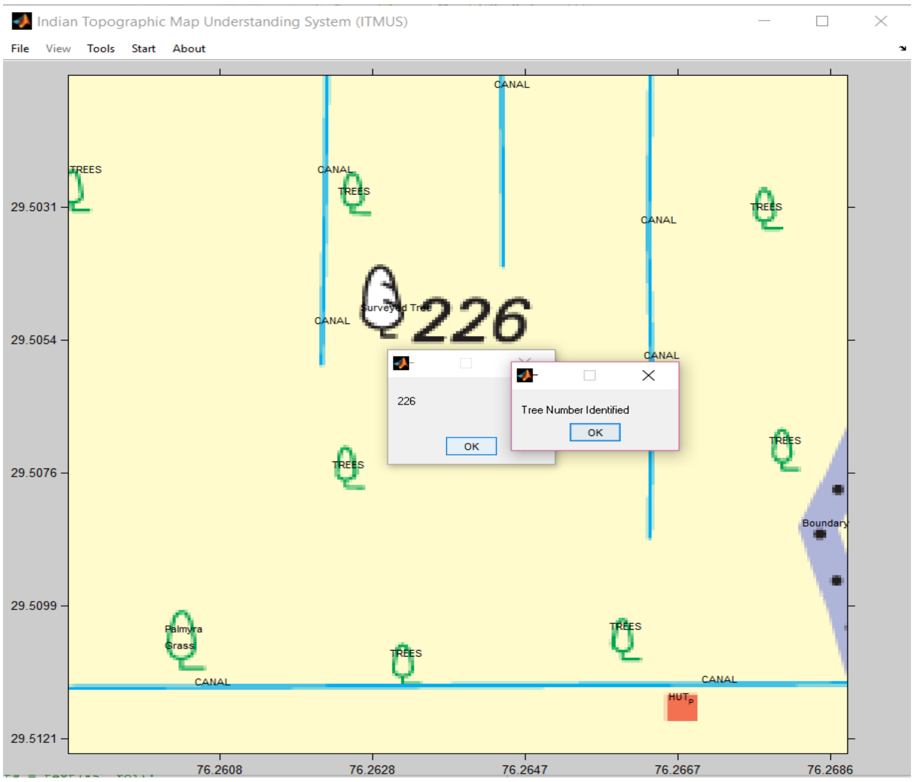



*Figure 5.27 Interpreted Indian topographic map region, random selection (RS1)*

### 5.4.8 Map Layer Analysis Module

For the layer based understanding of topographic maps, a separate module has been developed as a map layer analysis module. Layer based analysis has been facilitated by preprocessing module and color layer separation module. The intelligent module has been proposed in the previous section for the interpretation of symbols. The aggregation of symbols into a single class or category has been done internally and no separate function needs to be implemented. The numerical analysis of layers has also been written in Map Object Structure Description Database. Also, map layer comparison of the system has been generated.Layer and ground truth in respect to success and failure in layer extraction have been demonstrated by overlaying system generated layer and ground truth layer. The logical AND operation returns map objects, which provides the important measure of layer extraction.

### 5.4.9 Map Spatial Analysis Report Generation

The interpretation and resulting understanding of topographic map consist of classification result along with spatial, topographic and structural details. The classification result includes the symbol's semantic meaning derived from other modules. Spatial details such as latitude and longitude, topographic details such as the general shape of a symbol, structural details which include 10 invariant shape feature measured in another module needs to be recorded and maintained. The map spatial analysis, generates reports, to create object description in the separate spreadsheet file, which may be used as a geospatial topographic map database for several geolocation based application software. Also, development of module further generates text file having a summarization of map understanding with filing symbol names and locations. The sample text report has been shown in Figure 5.28 and Figure 5.29. This information has been used for the accuracy assessment module.

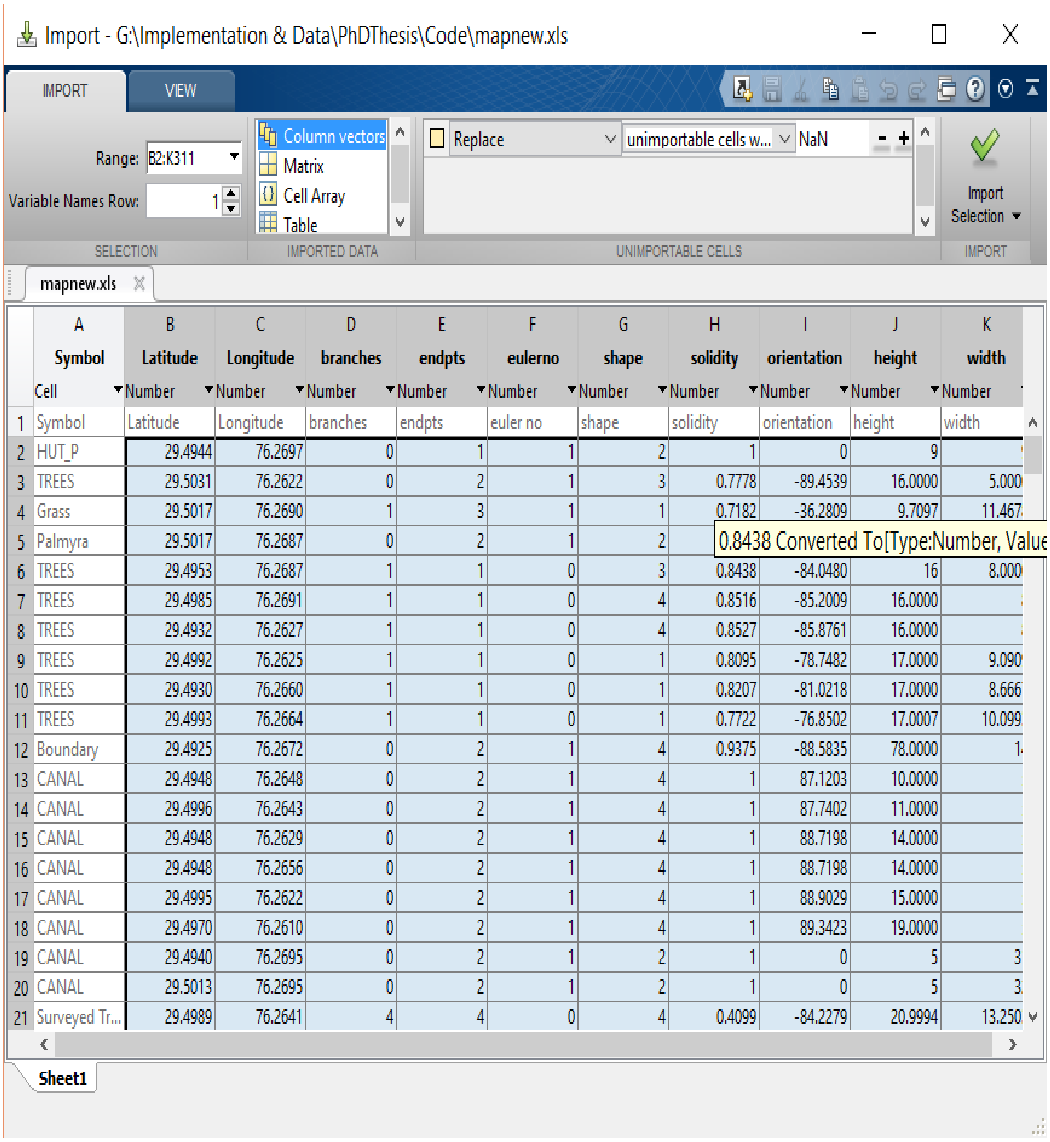
```
symbol name:  HUT_P ; location:  197 , 235
 symbol name:  TREES ; location:  1 , 36
 symbol name:  Grass ; location:  32 , 215
 symbol name: Palmyra ; location:  32 , 209
 symbol name:  TREES ; location:  178 , 208
 symbol name:  TREES ; location:  106 , 218
 symbol name:  TREES ; location:  224 , 50
 symbol name:  TREES ; location:  89 , 44
 symbol name:  TREES ; location:  230 , 138
 symbol name:  TREES ; location:  87 , 147
 symbol name: Boundary ; location:  241 , 169
 symbol name:  CANAL ; location:  189 , 106
 symbol name:  CANAL ; location:  81 , 93
 symbol name:  CANAL ; location:  188 , 55
 symbol name:  CANAL ; location:  189 , 126
 symbol name:  CANAL ; location:  82 , 36
 symbol name:  CANAL ; location:  140 , 4
 symbol name:  CANAL ; location:  208 , 228
 symbol name:  CANAL ; location:  42 , 229
 symbol name: Surveyed Tree ; location:  96 , 88
```

***Figure 5.28 Map spatial analysis report*** *(53C7Five.txt)*

### 5.4.10 Map Symbol Accuracy Assessment Visualisation

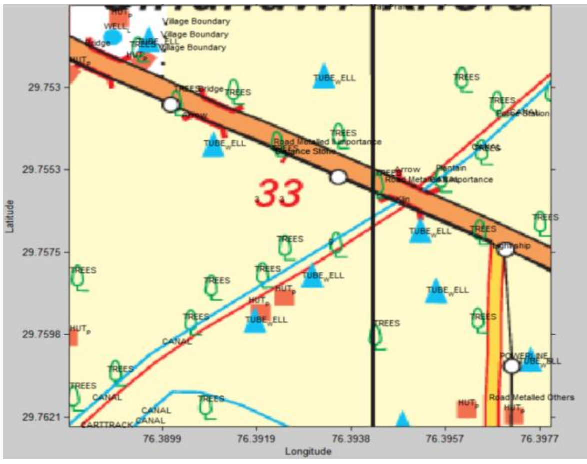
The map symbol accuracy assessment module design incorporates comparison between system generated map understanding summary with their local coordinated and standard metafile generated by Survey of India in Microstation software.This module maintains a table, keeping track of the recognized symbols, their location and number of instances occurred in training map data as well as checking map data.

In Figure 5.30 (a) and 5.30 (b), map interpretation (i-map), and assessment of map interpretation of the sample OSM topographic map namely 53C7Five are provided. The third column denotes actual symbols present and fourth column denotes symbols interpreted by the ITMUS system at the geolocations. If column 3 and column 4 are compared then it can be seen that system has a very good capability to understand topographic map symbols. Thus accuracy assessment table does a job of providing ITMUS interpreted symbols and symbols reference data.




| | A | B | C | D | E | F | G | H | I | J | K |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Symbol | Latitude | Longitude | branches | endpts | eulerno | shape | solidity | orientation | height | width |
| | Cell | Number | Number | Number | Number | Number | Number | Number | Number | Number | Number |
| 1 | Symbol | Latitude | Longitude | branches | endpts | euler no | shape | solidity | orientation | height | width |
| 2 | HUT_P | 29.4944 | 76.2697 | 0 | 1 | 1 | 2 | 1 | 0 | 9 | |
| 3 | TREES | 29.5031 | 76.2622 | 0 | 2 | 1 | 3 | 0.7778 | -89.4539 | 16.0000 | 5.000 |
| 4 | Grass | 29.5017 | 76.2690 | 1 | 3 | 1 | 1 | 0.7182 | -36.2809 | 9.7097 | 11.467 |
| 5 | Palmyra | 29.5017 | 76.2687 | 0 | 2 | 1 | 2 | | | | |
| 6 | TREES | 29.4953 | 76.2687 | 1 | 1 | 0 | 3 | 0.8438 | -84.0480 | 16 | 8.000 |
| 7 | TREES | 29.4985 | 76.2691 | 1 | 1 | 0 | 4 | 0.8516 | -85.2009 | 16.0000 | |
| 8 | TREES | 29.4932 | 76.2627 | 1 | 1 | 0 | 4 | 0.8527 | -85.8761 | 16.0000 | |
| 9 | TREES | 29.4992 | 76.2625 | 1 | 1 | 0 | 1 | 0.8095 | -78.7482 | 17.0000 | 9.090 |
| 10 | TREES | 29.4930 | 76.2660 | 1 | 1 | 0 | 1 | 0.8207 | -81.0218 | 17.0000 | 8.666 |
| 11 | TREES | 29.4993 | 76.2664 | 1 | 1 | 0 | 1 | 0.7722 | -76.8502 | 17.0007 | 10.099 |
| 12 | Boundary | 29.4925 | 76.2672 | 0 | 2 | 1 | 4 | 0.9375 | -88.5835 | 78.0000 | 1 |
| 13 | CANAL | 29.4948 | 76.2648 | 0 | 2 | 1 | 4 | 1 | 87.1203 | 10.0000 | |
| 14 | CANAL | 29.4996 | 76.2643 | 0 | 2 | 1 | 4 | 1 | 87.7402 | 11.0000 | |
| 15 | CANAL | 29.4948 | 76.2629 | 0 | 2 | 1 | 4 | 1 | 88.7198 | 14.0000 | |
| 16 | CANAL | 29.4948 | 76.2656 | 0 | 2 | 1 | 4 | 1 | 88.7198 | 14.0000 | |
| 17 | CANAL | 29.4995 | 76.2622 | 0 | 2 | 1 | 4 | 1 | 88.9029 | 15.0000 | |
| 18 | CANAL | 29.4970 | 76.2610 | 0 | 2 | 1 | 4 | 1 | 89.3423 | 19.0000 | |
| 19 | CANAL | 29.4940 | 76.2695 | 0 | 2 | 1 | 2 | 1 | 0 | 5 | 3 |
| 20 | CANAL | 29.5013 | 76.2695 | 0 | 2 | 1 | 2 | 1 | 0 | 5 | 3 |
| 21 | Surveyed Tr... | 29.4989 | 76.2641 | 4 | 4 | 0 | 4 | 0.4099 | -84.2279 | 20.9994 | 13.250 |

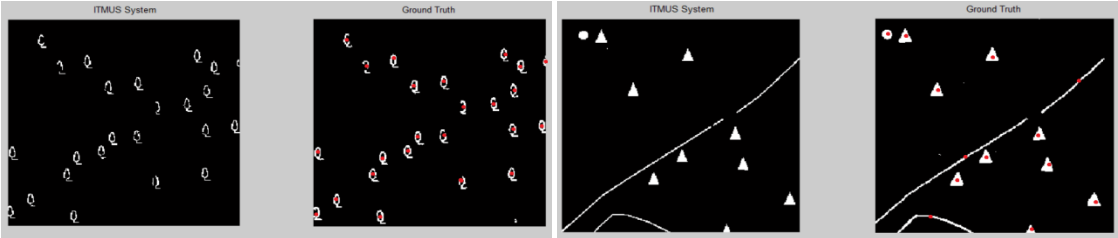
*Figure 5.29 Map Understanding report in excel spreadsheet*




|  | Symbol | Instances(Standard) | Instances(Calculated) |
|---|---|---|---|
| 1 | 9 | 0 | 1 |
| 2 | Arrow | 0 | 2 |
| 3 | Bridge | 2 | 2 |
| 4 | CANAL | 7 | 7 |
| 5 | CARTTRACK | 1 | 1 |
| 6 | Distance Stone | 1 | 2 |
| 7 | HUT_P | 8 | 8 |
| 8 | Klin | 0 | 1 |
| 9 | Light ship | 0 | 1 |
| 10 | Map Frame | 1 | 1 |
| 11 | POWERLINE... | 1 | 1 |
| 12 | Plantain | 1 | 1 |
| 13 | Police Station | 1 | 1 |
| 14 | Road Metalle... | 3 | 2 |
| 15 | Road Metalle... | 3 | 1 |
| 16 | TREES | 22 | 21 |

(a) (b)

***Figure 5.30 (a) Map Region 53C7five sample Understanding, (b) Map object instances in reference data and interpreted data***




**(a)** **(b)**

***Figure 5.31 ITMUS extracted map layer compared with Manual traced layer and red dots show correct object extraction, (a) Green layer: left side- system extracted and right side- manually delineated/extracted, (b) Blue layer: left side- system extracted and right side- manually delineated/extracted***

### 5.4.11 Map Layer Comparison Visualisation and Accuracy Assessment

The module for the assessment of the map layer extraction provides a framework to load the system generated thematic layers of topographic maps and manual delineated ground truth layer data of the same area. It prepares binary mask using manually delineated layer data. Further, this module implements overlaying operation between the system and manual results. The layer recognition performance has been quantified using area extraction measure. The correctly recognized map layers have been recognized and verified manual observation as well as overlaying of manual delineated layers and ITMUS generated layers.

Based on this, misclassification cost or penalty matrix (as discussed in section 3.6) has been determined and index for low, medium and high misclassification has been derived.The snapshot of assessment of layer extraction of ITMUS has been given in Figure 5.31. It has been used to evaluate ITMUS layer recognition performance,which is briefed in the next chapter in section 6.4.2.

## 5.5 DISCUSSION

This chapter describes the method used in the present research work. It has also been described as the methodology by proceeding to the ANFIS model to treat the topographic map for extracting relevant information and interpreting map objects. The developed system has integrated human based and machine (computer) based *map understanding process* using the combination of feature based and learning based techniques

In the developed system, the morphological operations divide the map image array into contiguous groups of elements and measured numerically later. Connected components labeling spread labels within these groups. Pixel thresholding and gray index thresholding segmentation establishes color based layers by computing histograms within small, overlapping windows for identification of local features which are to be labeled. The shape and structure features such as area, solidity, eccentricity, Euler number have been measured to describe each object in order to produce feature description. LUS implements legend knowledge base which has been further used by MUS. Thus, the legend features have been categorized in different datasets based on color and shape peculiarity by assigning object code to the semantic meaning of the legend. This object code has been used as the target output for ANFIS classifiers working under MUS kernel.

The system utilizes the approach of map layer separation. For every map layer, spatial attributes, and geographic attribute has been used to understand the map. Based on relevant rules for automatic legend understanding and adaptive learning for map object understanding multi-step approach have been adopted. A rule reduction approach achieves a method to understand legend set. Next MUS has been implemented which utilizes obtained knowledge in creating the initial training set. Then, 9 ANFIS models have been designed to implement MUS kernel which provides an environment to design initial FIS and ANFIS learning/training. The developed system possesses a learning module which incorporates the learning algorithm that has the ability of quickly creating fuzzy rules from a set of training data and tuning them with modification of membership functional parameters. Learn module enables the system to learn the shape, color of object components and location or association of objects of an each map symbol and associate it with particular legend or object type label. The best ANFIS models have been selected based on RMSE values. The major outcomes of the ITMUS are the interpreted map, thematic map layer information and geolocation based layer as well as map object database. The interpreted map (i.e. i-map) has been used for map understanding while thematic layers have been important for the layer-wise analysis of topographic map. Map object databases containing object's geometric, geo-location properties and their values may be used for vectorization, automatic map updating or map generalized applications. All these outputs have been feasible to store, explore and which may be further used by Geoinformation based system. The ITMUS has been developed using MATLAB (The Mathwork Inc.).The developed system has the ability to perform an assessment of layer extraction using manually delineated layer data. The system has been added to an assessment module to show the correct understanding of map objects from the testing map regions in comparison with metadata developed by the Survey of India. The working of the developed system provides procedural and operational details of Indian topographic map understanding system. The completeness and correctness of ITMUS have been demonstrated as well as evaluation and validation have been carried out which is reported in the next chapter.

# CHAPTER 6
# WORKING AND VALIDATION OF THE SYSTEM

## 6.1 INTRODUCTION

The successful working and validation of Indian topographic map understanding system (ITMUS) demonstrate the completeness of the development. The working of the system has been based on a combination of neural network and fuzzy theory, commonly known as Neuro-fuzzy computing, which the one of the soft is computing hybrid technique that has been successfully incorporated. The inherent characteristics of the Neuro-fuzzy system such as parallelism, robustness, and learning and classification abilities allow ITMUS to handle vague and imprecise feature dataset of map objects [211]. In order to deal with varying map symbols and to obtain robust identification of the semantic description of topographic map symbols, a soft computation based ITMUS has been developed [337, 338]. As discussed earlier, the working of the system has been based on hybrid approach which have been implemented using adaptive Neuro-fuzzy system (ANFIS) to make the computer to perceive legends structure, learn it and use learnt knowledge for map reading. If some new instances have occurred, then make the computer to adapt their knowledge to enhance the performance [235]. In the developed system, Sugeno integrals [115] have been used to model ANFIS. Its architecture has distinct nodes such as to accommodate object's features as antecedent clauses; for conjunction operators, and for their physical meaning (code assigned) as consequent clauses. The system's functioning has been highly relied on legend understanding subsystem (LUS) and its integration with map understanding subsystem (MUS). The LUS creates initial knowledge about legend set. However, this knowledge has been used as initial training set to create an initial FIS rule set which further gets refined and tune by MUS through offline learning.

The performance evaluation of the topographic map understanding system highly relies on a number of experimental observations, which requires much investigation on test images. It has been highly crucial for subjecting performance based on test images as each test image shows high variation in complexity. In this study, the correct recognition rate against the size of test map images has been considered. The complexity of the topographic map affects the recognition performance, which may vary from 75% to almost 100%. The

LUS and MUS have been evaluated separately. The manual checking has been considered as criteria for evaluation. The ITMUS has been tested on five Geotiff Indian topographic maps.

In LUS, the legend understanding handler performs acquisition of legend set consisting of 117 legends. Legend understanding kernel interprets the legend set. The LUS has been tested on legend sets of 53C7, 53F6, 53F7, 53F11, 53K1 numbered topographic maps. Different case studies have been performed to evaluate the performance of MUS. Each case study has considered training and testing set, whose specification is given further in Table 6.3. Every case study has been carried out to evaluate and validate system with respective to different output in response to different parameters. The ITMUS has been trained for various sample regions selected from 53C7 and 53K1 OSM topographic map. However, OSM 53C7, 53F6, 53F7, 53F11 and 53K1have been used to carry out a different case study in which test map regions have been selected from this map either from the same region or from different regions. The testing regions selected from 53C7 and 53K1 have been sufficiently different from training regions. The OSM topographic maps 53F6, 53F7, 53F11 have been treated as an independent topographic map data and have been used as a testing and checking data to evaluate ITMUS.

In Section 6.2, details of data used for development of the system as well as validation of the system are described. Section 6.3 describes the working of the system where subsections provide detail working of legend understanding subsystem and map understanding subsystem. Through section 6.4 to section 6.7, details of different case studies carried out have been reported and discussed. The evaluation of the result has given in respective subsections of each case study. For each case study, ITMUS has been assessed and validated using different parameters and qualitative and statistical measures. Lastly, in Section 6.8, working and validation of the system is summarized.

## 6.2 DATA

To develop and validate ITMUS, five GeoTiff Open series Indian topographic maps (in the scale of 1:50,000) prepared by the Survey of India, Dehradun have been used. The study area considered includes five different territories, namely Jind (Haryana), Sirmaur (Himachal Pradesh), Yamunanagar (Haryana), Boundary area of Sirmaur, (H.P.), Dehradun, (U.K.), Saharanpur, (U.P.), Yamunanagar, (Haryana), Haridwar, (Uttarakhand). The maps belong to the above-mentioned territories in India, which have been identified by the old sheet numbers 53C7, 53F6, 53F7, 53F11, 53K1 and new OSM numbering H43Q7, H43L6, H43L7, H43L11, H44M1 respectively have been used. The details of the study area and data (topographic map) have been given in Table 6.1.

### 6.2.1 Geotiff Open Series Indian Topographic Maps (OSM)

A geo-referenced color raster data have been defined as GeoTiff OSM. Map image coordinates have been related to the ground coordinate based on the information stored in the geo-referenced dataset. These map images have been geo-referenced using Universal Transverse Mercator (UTM) projection system and WGS datum. The OSM map standardizes colors and hence the scanner limitations and artifacts have been avoided. This data has been in the native format that before printing it on a paper. The SOI GeoTiff OSM product consists of two types of physical files: TIFF image along with reference matrix (in current work it has been taken as an input) and a metadata file in text format (in current work it has been taken as reference data for accuracy assessment) which has been created manually. The associated image ( .TIF), includes an intelligent dataset name (DSN) consisting of the spatial location of the file. The content of topographic map has been augmented by their spatial and categorical description. But this has been created by human-computer intervention. Such an information has been visible or accessible on geobased software or Microstation software otherwise, TIFF is used for rendering or display purpose. The metadata/file creation process has been tedious and time-consuming, requiring substantial labor to process a single map sheet. Hence, the automated labeling or binding of semantic meaning to map entity has been essential and in need.

A DRG is resulting from scanning a paper SOI topographic map. These maps have been scanned at 200 dpi by Survey of India (SOI) but may include printing as well as scanning environment artifacts. Paper-based topographic maps have rarely used by mapping agencies as well as it has less practical importance for their distant users. On the other hand; OSM digital raster map image consists of standardized color and usually used to avoid scanning environment, paper quality variance, and their limitations. DRG information extraction techniques may perform well if the images are scanned at high resolution and by quality scanners otherwise proves ineffective if contains aliased and false colors. To overcome this difficulty as well as considering the practical importance of OSM DRG, it has been used in the present study. As said earlier, this map is UTM projected and geo-referenced to the earth's surface at WGS 84 datum. GIS applications typically use such files. Their analysis has found applications in map update and map generalization also. So, its automatic interpretation will serve an excellent solution for automatic information acquisition and map layer information extraction with their geolocations.

***Table 6.1 Data sheet numbers, OSM numbers, territory name and other details***

| Sr. No. | Data Sheet Number | | Latitude | | Longitude | | Territory Name | Scale | Edition |
|---|---|---|---|---|---|---|---|---|---|
| | International Numbering System | OSM Numbering System | To | From | To | From | | | |
| 1 | 53C/7 | H43Q7 | 29D30 M | 29D15 M | 76D30 M | 76D15 M | Jind Haryana | 1:50000 | 2007 |
| 2 | 53F/6 | H43L6 | 30D45 M | 30D30 M | 77D30 M | 77D15 M | Sirmaur Himachal Pradesh | 1:50000 | 2011 |
| 3 | 53F/7 | H43L7 | 30D30 M | 30D15 M | 77D30 M | 77D15 M | Yamunanagar, Haryana | 1:50000 | 2009 |
| 4 | 53F/11 | H43L11 | 30D30 M | 30D15 M | 77D45 M | 77D30 M | Boundary area of Sirmaur, H.P., Dehradun, U.K., Saharanpur, U.P., Yamunanagar, Haryana | 1:50000 | 2009 |
| 5 | 53K/1 | H44M1 | 30D00 M | 29D45 M | 78D15 M | 78D0M | Haridwar, Uttarakhand | 1:50000 | 2011 |

## 6.3 WORKING OF THE SYSTEM

ITMUS has been developed for the automatic understanding of Indian topographic maps. The functioning of ITMUS has been based on two main subsystems: Legend Understanding Subsystem (LUS) and Map Understanding Subsystem (MUS). The novel approach which is based on human topographic map understanding requires the use of a priori knowledge base containing features of legends and meaning associated with the legends; where features have been calculated and measured by various morphological operations. Legend understanding subsystem utilizes the method based on the matching of recognized shape features using static rules to deduce the meaning of the legend. The developed map understanding subsystem may deal with the complexity and interconnected objects of topographic maps. The initial FIS has been designed for initial rule generation. Further, the designed FIS has been trained using legend set training data. Resulting ANFIS structure has been evaluated for training, testing and validation data.

As discussed, the working of the ITMUS has been divided into two parts depending on the constituent subsystems: first is working of LUS and the second is working of MUS. Legend Understanding Subsystem has been provided with Geotiff Indian Topographic maps. The LU Handler which controls the LU subsystem first scans Legend set region in the map. The legend set region has been further processed and analyzed by system methodically as shown in Figure 6.1. Each legend in legend set has been identified in color, structure and shape parameters. The shape has been recognized into its structure parameters by recursion. It has been done by binding If-Then rules with semantic meaning of the legend. In this conditional pattern matching, the shape parameters in conditional expressions have been evaluated and if they evaluate as true, then the semantic meaning or description of legend present on conclusion part has been returned. Thus, legend set has been interpreted and understood by ITMUS. The LU handler creates legend set structure description containing its shape features and their values. The second important component of ITMUS is MUS, which has been controlled by Map understanding (MU) handler. It divides the legend description data set into 9 training set. MUS kernel which acts as a backbone of MUS utilizes sets of training data to create an initial Fuzzy inference system (FIS). The initial FIS has been trained to generate multi-model adaptive Neuro-fuzzy system. Once a region of interest (ROI) has been selected for analysis, previously trained model evaluates the obtained shape parameters of the objects in the region under processing to make the computer understand ROI.

As Indian topographic map understanding has comprised of two major subsystems, two main outputs have been obtained from respective subsystems. The LUS acquires the legend set from GeoTiff topographic map and generates interpreted form of legend set. The MUS acquires random region of interest from a topographic map and gives interpreted region, extracted thematic layers and geo-location based map as well as map layer data set as a major outcome. The working of the subsystems along with obtaining results and accuracy assessment of each subsystem have been provided in forthcoming subsections.

### 6.3.1 Legend Understanding Subsystem (LUS)

The LUS has been based on the conditional rule reduction of recognized shape primitives and features to deduce the meaning of the legend. The legend set region has been processed and analyzed by the system. Each legend in legend set has been identified for color, structure and shape parameters. The shape has recognized into structural parameters by recursion. In conditional rule matching, the shape parameters in conditional expressions evaluate true and returns the semantic meaning of the legend.

The LUS has been tested on 5 Geotiff topographic maps successfully. Figure 6.2, part (a) shows the original legend set and part (b) shows the interpreted legend set. The LUS takes legend set as an input given from the topographic map. It reads the legend from legend set and provides annotated legend set as an output. System understood the legends by color and structural properties. The legend meaning is deduced based on static rules reduction. LUS is also responsible for implementation of initial legend structure database, which has been utilized as an initial knowledge for rule generation. The snapshot of initial legend knowledge data set (i.e. initial training data set) has been given in Figure 6.3. System stores shape and structural feature measurements of each legend. Some sample region interpretation have been shown in Figure 6.5. For the study and development of the system, topographic maps have been selected and their legend sets have been processed and measured against a set of features. Each legend set consists of 117 legends. Legends set of each map has been similar in color as well as in the structure of the legends. For initial training set formation, five legend sets have been measured and interpreted. Their shape description has been associated with the set of eight representative features and further treated as expected or target output for ANFIS learning.

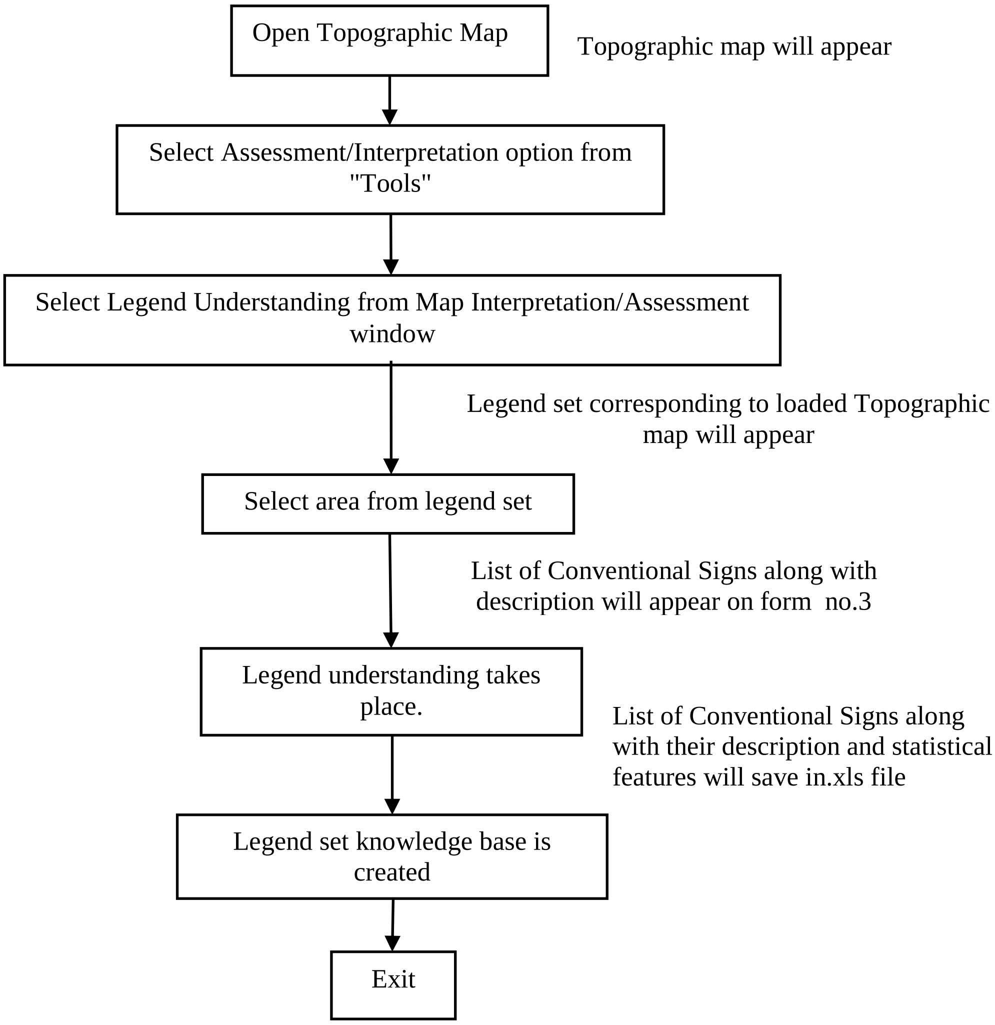
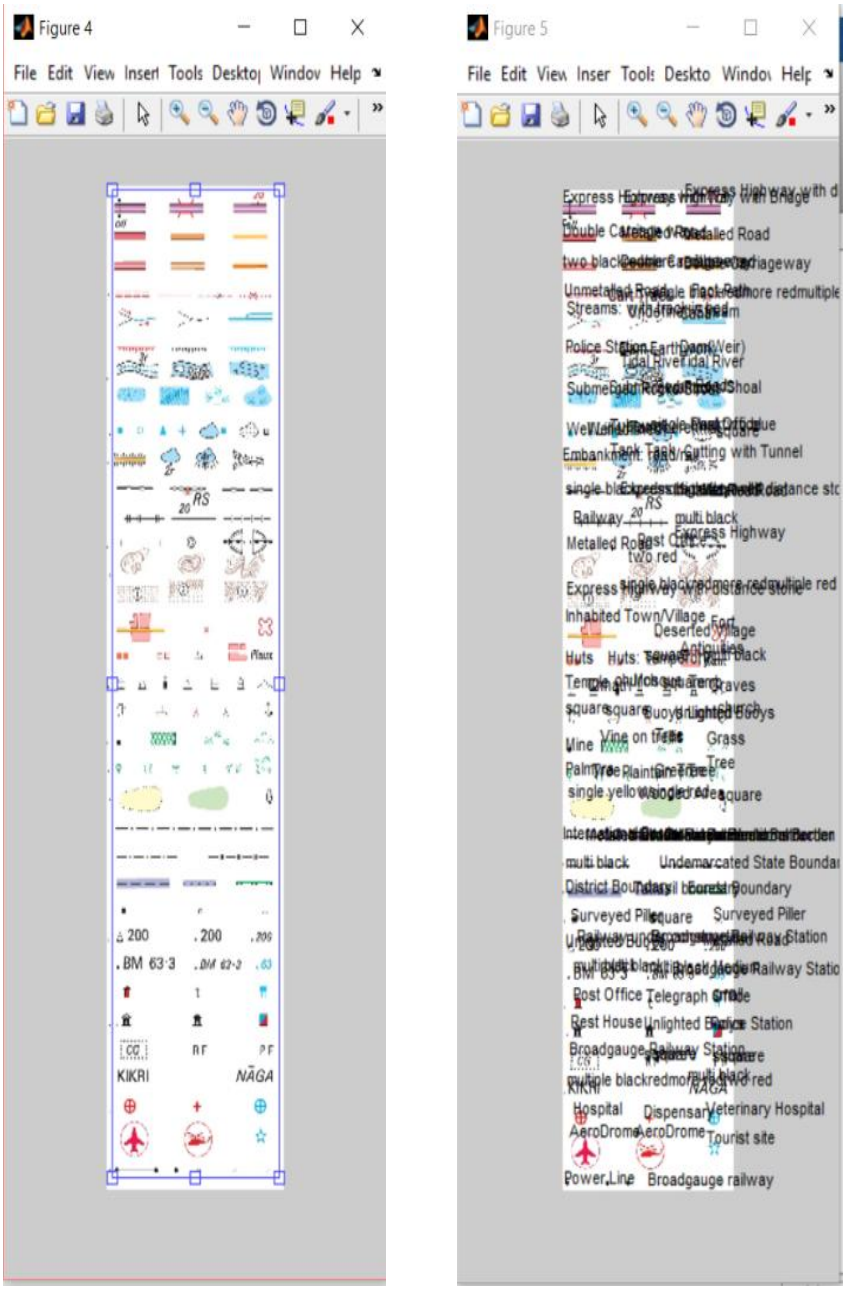



***Figure 6.1 Working flow graph of Legend Understanding Subsystem (LUS)***

### 6.3.1.1 LUS accuracy assessment and validation

The Indian topographic map legend set is consisting of 117 legends. Legend set shows graphical symbols for map objects and associated semantic description or meaning. These legends are the key to reading topographic map in both, either manual map reading or automated machine map reading. As five topographic maps of 5 different territories have been selected for the study, against which the performance of the developed system has been tested.




*(a)* *(b)*

***Figure 6.2 (a) Conventional Legends set, (b) Interpreted Legends set***

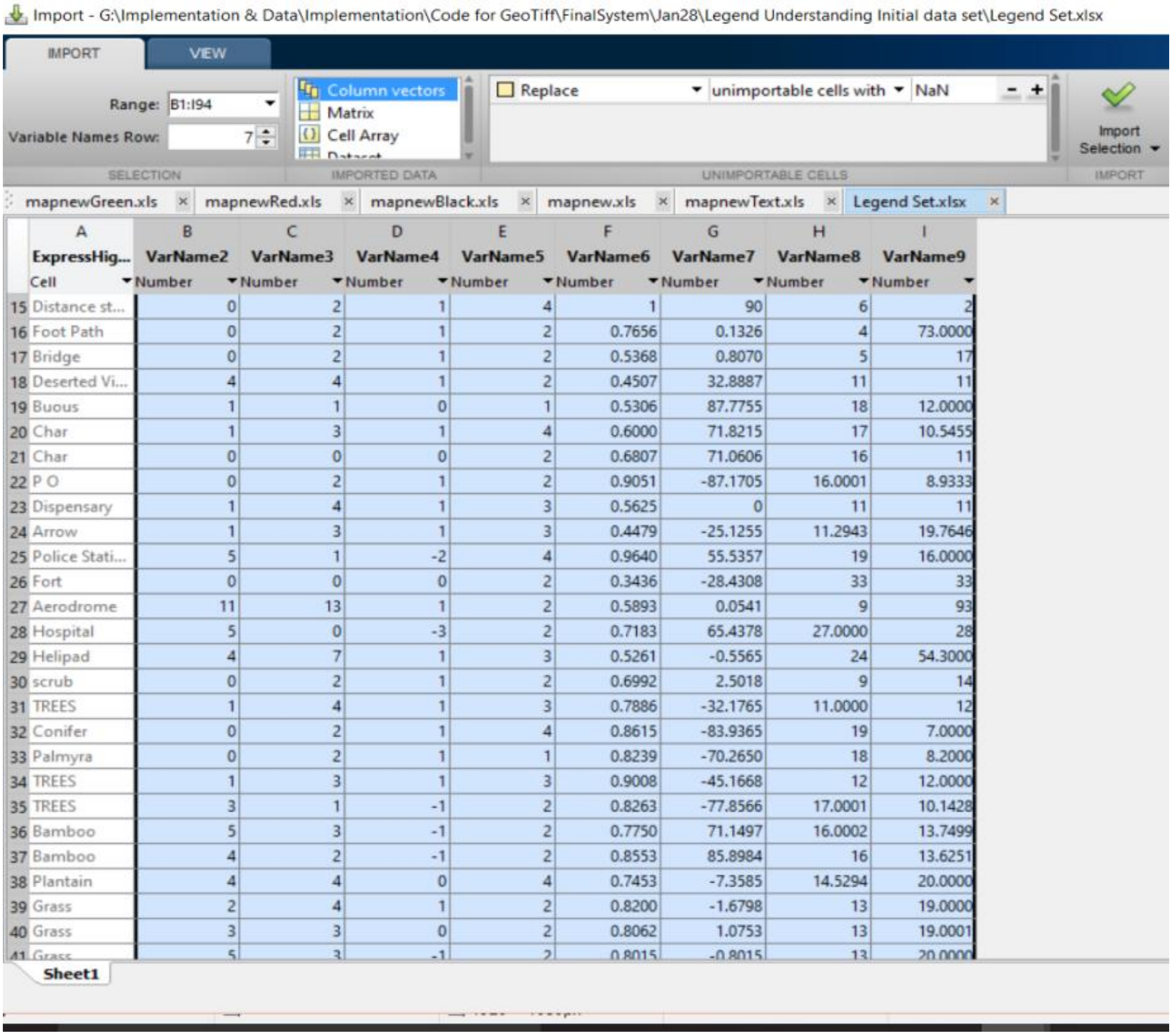
To assess the performance of LUS, a number of correct recognitions has been used as a performance measure. The correct recognition results have been validated using human interpretation result for legend set. The recognitions performed by human have been used as criteria for evaluation [190]. In the Figure 6.4 part (a1-a2) shows the Legends set depicted on the topographic map, part while part (b1) - (b4) shows legends set interpretation stored in .pdf file format. In Figure 6.5, part (a) shows original legend set also along with system interpreted samples of legends from selected regions and (b) - (c) gives system interpreted samples of legends from selected regions. The percentage of accuracy of LUS has been calculated by a formula which has been discussed in section 3.6.

*Accuracy = (Number of correct legend recognition/Total number of legends)*100*

*Average Accuracy = (Sum of the legend recognition result of all topographic map legend sets/Number of topographic maps)*

*= (90.00+89.74+85.47+86.32+90.59/5)*

*= 88.424%*




| | A | B | C | D | E | F | G | H | I |
|---|---|---|---|---|---|---|---|---|---|
| | ExpressHig... | VarName2 | VarName3 | VarName4 | VarName5 | VarName6 | VarName7 | VarName8 | VarName9 |
| | Cell | Number | Number | Number | Number | Number | Number | Number | Number |
| 15 | Distance st... | 0 | 2 | 1 | 4 | 1 | 90 | 6 | 2 |
| 16 | Foot Path | 0 | 2 | 1 | 2 | 0.7656 | 0.1326 | 4 | 73.0000 |
| 17 | Bridge | 0 | 2 | 1 | 2 | 0.5368 | 0.8070 | 5 | 17 |
| 18 | Deserted Vi... | 4 | 4 | 1 | 2 | 0.4507 | 32.8887 | 11 | 11 |
| 19 | Buous | 1 | 1 | 0 | 1 | 0.5306 | 87.7755 | 18 | 12.0000 |
| 20 | Char | 1 | 3 | 1 | 4 | 0.6000 | 71.8215 | 17 | 10.5455 |
| 21 | Char | 0 | 0 | 0 | 2 | 0.6807 | 71.0606 | 16 | 11 |
| 22 | P O | 0 | 2 | 1 | 2 | 0.9051 | -87.1705 | 16.0001 | 8.9333 |
| 23 | Dispensary | 1 | 4 | 1 | 3 | 0.5625 | 0 | 11 | 11 |
| 24 | Arrow | 1 | 3 | 1 | 3 | 0.4479 | -25.1255 | 11.2943 | 19.7646 |
| 25 | Police Stati... | 5 | 1 | -2 | 4 | 0.9640 | 55.5357 | 19 | 16.0000 |
| 26 | Fort | 0 | 0 | 0 | 2 | 0.3436 | -28.4308 | 33 | 33 |
| 27 | Aerodrome | 11 | 13 | 1 | 2 | 0.5893 | 0.0541 | 9 | 93 |
| 28 | Hospital | 5 | 0 | -3 | 2 | 0.7183 | 65.4378 | 27.0000 | 28 |
| 29 | Helipad | 4 | 7 | 1 | 3 | 0.5261 | -0.5565 | 24 | 54.3000 |
| 30 | scrub | 0 | 2 | 1 | 2 | 0.6992 | 2.5018 | 9 | 14 |
| 31 | TREES | 1 | 4 | 1 | 3 | 0.7886 | -32.1765 | 11.0000 | 12 |
| 32 | Conifer | 0 | 2 | 1 | 4 | 0.8615 | -83.9365 | 19 | 7.0000 |
| 33 | Palmyra | 0 | 2 | 1 | 1 | 0.8239 | -70.2650 | 18 | 8.2000 |
| 34 | TREES | 1 | 3 | 1 | 3 | 0.9008 | -45.1668 | 12 | 12.0000 |
| 35 | TREES | 3 | 1 | -1 | 2 | 0.8263 | -77.8566 | 17.0001 | 10.1428 |
| 36 | Bamboo | 5 | 3 | -1 | 2 | 0.7750 | 71.1497 | 16.0002 | 13.7499 |
| 37 | Bamboo | 4 | 2 | -1 | 2 | 0.8553 | 85.8984 | 16 | 13.6251 |
| 38 | Plantain | 4 | 4 | 0 | 4 | 0.7453 | -7.3585 | 14.5294 | 20.0000 |
| 39 | Grass | 2 | 4 | 1 | 2 | 0.8200 | -1.6798 | 13 | 19.0000 |
| 40 | Grass | 3 | 3 | 0 | 2 | 0.8062 | 1.0753 | 13 | 19.0001 |
| 41 | Grass | 5 | 3 | -1 | 2 | 0.8015 | -0.8015 | 13 | 20.0000 |

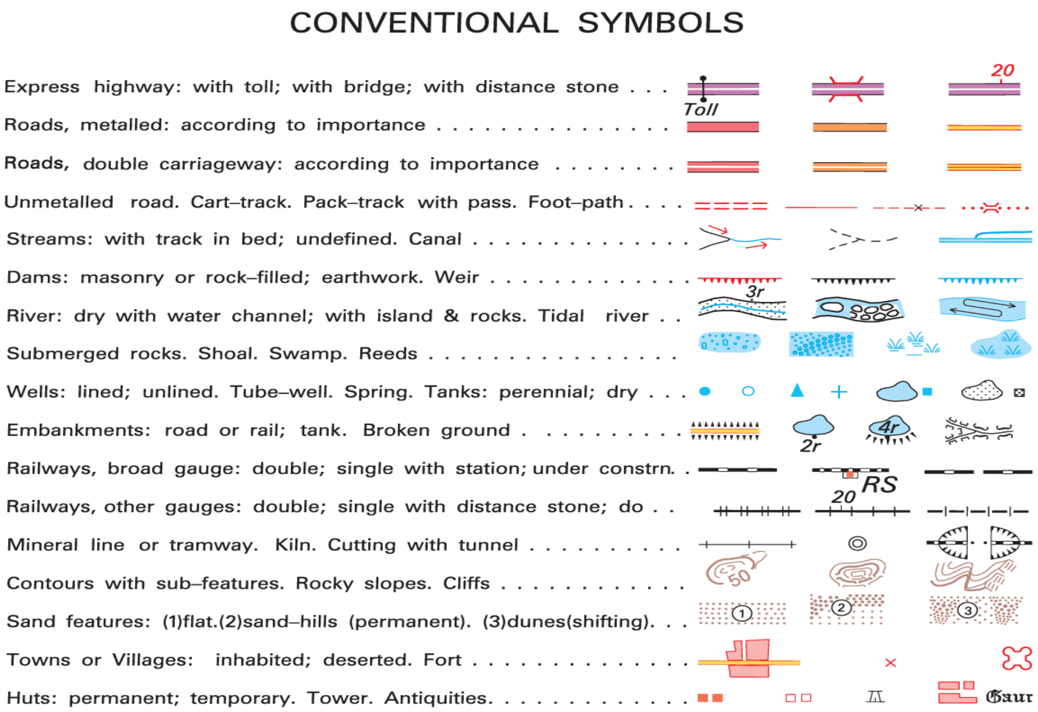
***Figure 6.3 Initial legend Knowledge data set generated by LUS***

The LUS also stores representative feature sets of each legend along with interpretation results (i.e. Semantic description) of legend. As specified previously, the evaluation of LUS is done by using manual interpretation. The legend set understanding results are reported in Table 6.2.

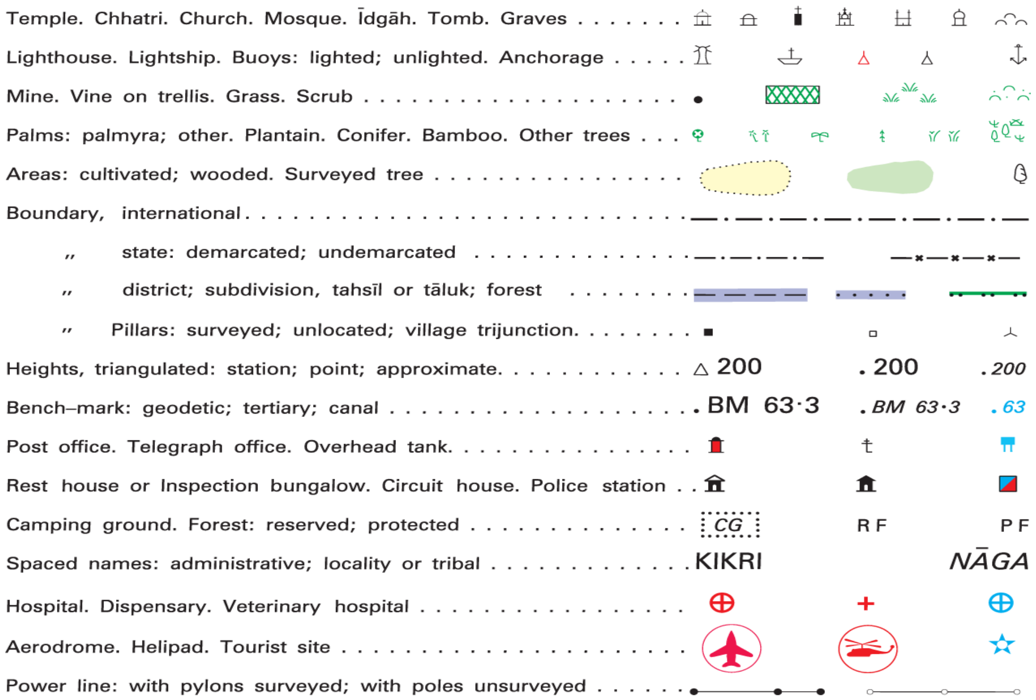
***Table 6.2 Legend Set Understanding Result***

| Legend set of | 53C7 Legend Set (117) | 53F6 Legend Set (117) | 53F7 Legend Set (117) | 53F11 Legend Set (117) | 53K1 Legend Set (117) |
|---|---|---|---|---|---|
| Recognized Correctly | 106 | 105 | 100 | 101 | 106 |
| Accuracy of recognition | 90.00% | 89.74% | 85.47% | 86.32 | 90.59 |

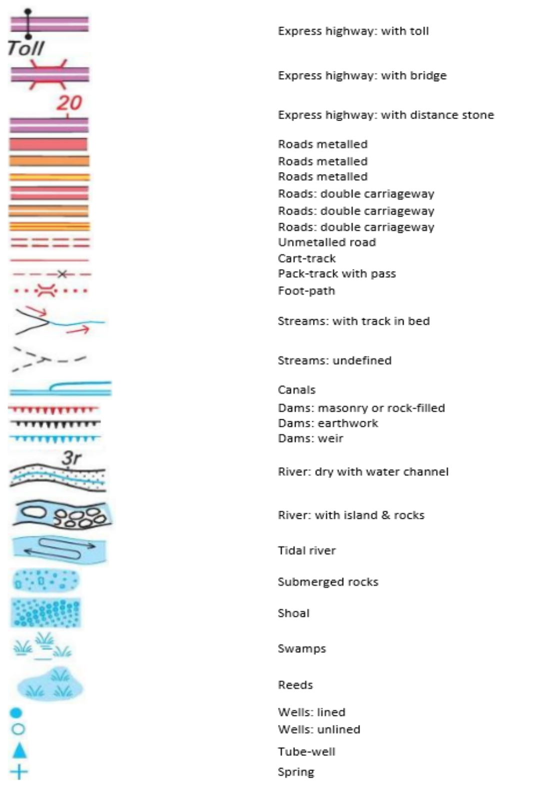
Total Legends in each set are 117.



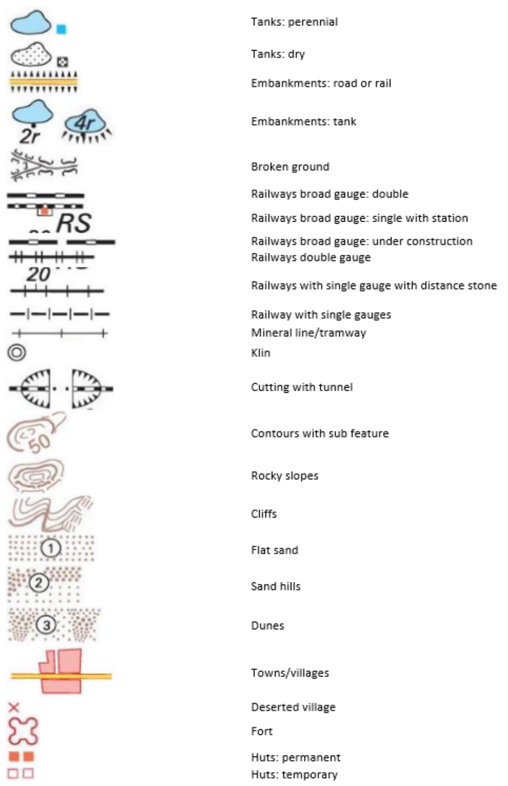

***(a1)***




***(a2)***




*(b1)*

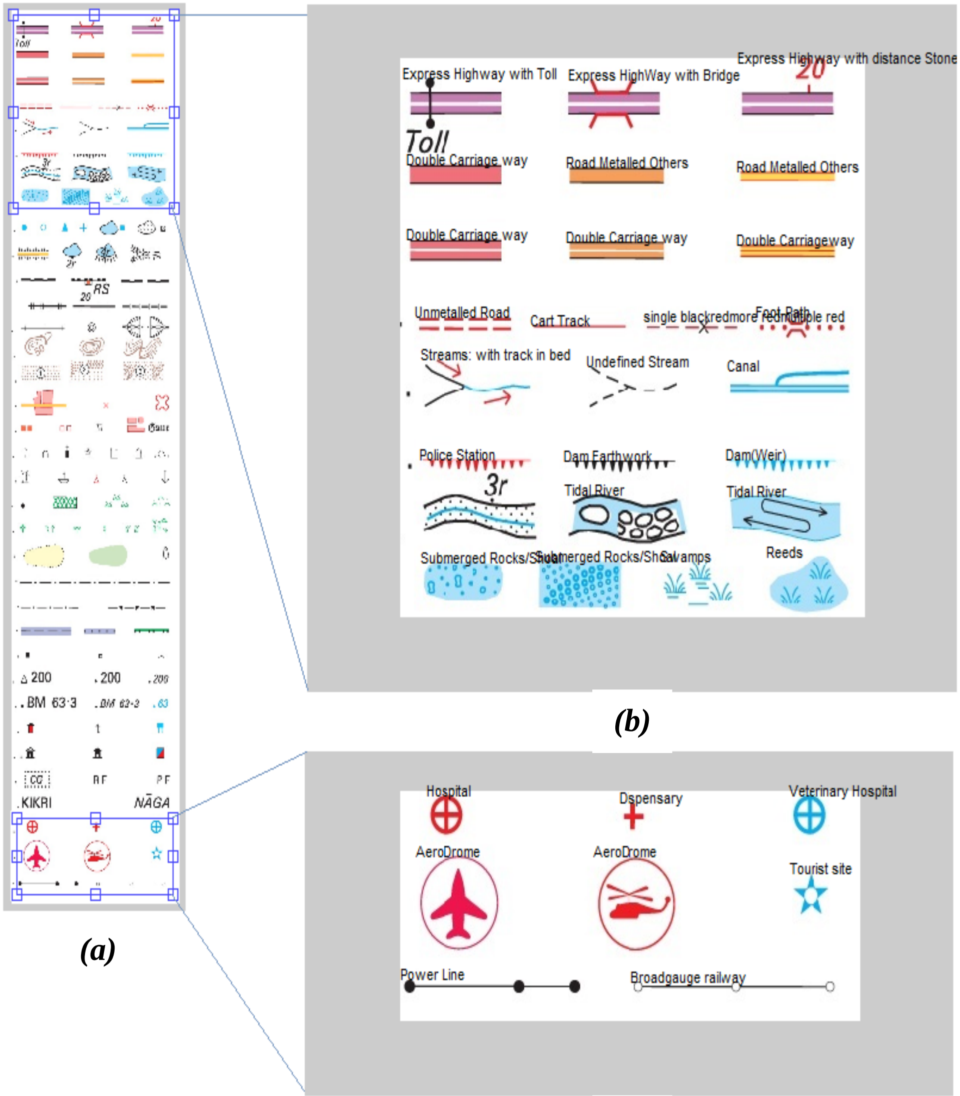



*(b2)*


*(b3)*


*(b4)*

***Figure 6.4 (a1) - (a2) Part of Legends set depicted on topographic map which is further used for assessment of LUS; (b1) - (b4) Legends set interpretation of corresponding legends set which is stored in .pdf file***




(a)

(b)

(c)

*Figure 6.5 (a) Original legend set and (b) and (c) system interpreted samples of legends from selected regions*

### 6.3.2 Map Understanding Subsystem (MUS)

The MUS has been controlled by MU handler which comprising of the sequence of map processing methods to generate map object description and learning based scheme to take up map object description as an input to deduce output based on previous learning is the backbone of the Indian topographic map understanding system. The MUS has been provided with a GeoTiff topographic map. The MU handler controls the selection of a region from the map and feeds the selected region to MUS. The MUS generates output in the form of interpreting maps (i-map), thematic map images as well as geo-location based information content.

MU handler further controls the region of interest selection from the topographic map which has been already loaded into the system. Map Geo converter module converts location coordinates (i.e. x-y values) of the area of interest to geo-coordinates (i.e. latitude and longitude values). MU handler segments a map region into layers based on color coding. The map object found in each layer has been processed to measure their shape features. These shape features of each map object in individual layers have been fed as input features to train model to determine expected output. The trained model has been evaluated on input data and predicts output. The output predicted by the intelligent model has been semantic meaning associated with that map symbol which has been found in the region of the map. The derived output, i.e. code associated with the semantic meaning of map object has been presented at the location coordinates, which lies at the centroid of the found object. The system is trained till it understands the new and random selection made on the map. The intelligent model stores the semantic description, measured shape parameter values and latitude-longitude information in geo-location based spatial dataset. The MU handler also utilizes the result obtained from intelligent kernel model to understand map in a layer-wise manner. The map objects have been recognized in the physical as well as in semantic layers. The MU handler stores obtained layers in image format as well as in table form with geo-location coordinates. The flow graph of map understanding subsystem has been shown in Figure 6.6.

MUS provide a high-level semantic description and meaning associated with topographic map objects. For example, the red color filled square has interpreted as Hut permanent. It also provides intermediate and high-level semantics or description like Building residential, and Building respectively. The MUS interprets lightship and lighthouse correctly, also understands it as a coastal object. Experimental results on topographic map data have proved that the proposed system has been effective in the automatic map understanding and thematic layer information extraction. MUS provide character/toponym understanding, but its understanding has constrained by the number of training samples in the training set. It has been found that the recognition rate of numbers and characters have been increased with the addition of the map text or toponym data samples in the training set. The MUS performance for toponym understanding depends on the number of characters in the model database. The MUS has not been evaluated separately for characters and numbers only. MUS has been tested and evaluated for the map region under test. As discussed earlier, for the study and development of the ITMUS, five Indian topographic maps of 5 different territories named as 53C7, 53F6, 53F7, 53F11, 53K1 have been selected as the main component on which complete development and working has been relaid. The details of GeoTiff topographic maps and their details have been given in Table 6.1.

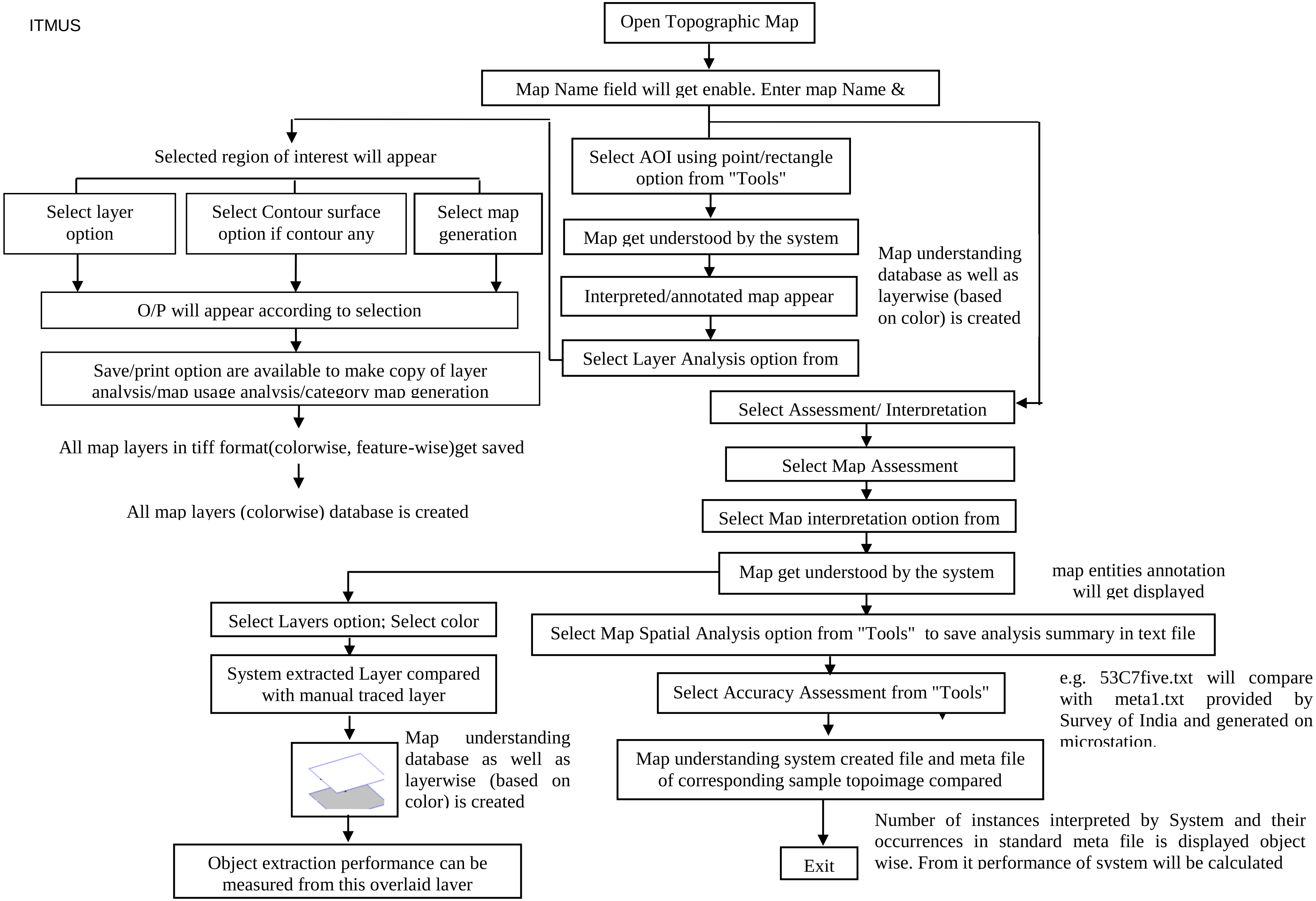



***Figure 6.6 Working Flow graph of Map Understanding Subsystem (MUS)***

The development of the system has been characterized by a novel approach in which human-based visual understanding has been used as a basic principle of topographic map understanding. The way in which topographic maps are interpreted by map readers with respect to their spatial content has been developed in an automated system which first reads the printed legends and afterward they understand map objects that might not be directly depicted on the map in the same form as found in legend set but still have been successfully understood. Thus, developed a system gains understanding about the map object by establishing correspondences between legend structural/shape parameter values and their formal description adaptively.

To evaluate and validate system with respective to a different output, different case studies have been done in response to different parameters. The ITMUS has been trained for various sample regions selected from 53C7 and 53F6 OSM topographic map. To carry out a different case study, map regions have been selected from 53C7, 53F6, 53F7, 53F11 and 53F6. The testing regions selected from 53C7 and 53F6 have been sufficiently different from training regions. The OSM topographic map data, namely 53K1, 53F7, 53F11, have been used as a *testing data* and *checking data* to check the generalization capability of MUS. The testing and checking regions have been selected from those maps, which are completely unseen to MUS. The details of testing sample image data whose selection have been made for different case study and characteristics regarding their domain selection have been summarized in Table 6.3. The total training and testing images used for case study I are 50 and 25 respectively. The training and testing images used in case study II are 25 and 25 respectively. In case study III, training inages used for training are 25 and the number of testing images are 5. Case study IV is based on 10 training images and 5 testing images. The details of number of training map region images and the number of testing map region images have been provided in Table 6.4.

***Table 6.3 Selection of testing image region data characteristics for different case studies***

| **Sr. No.** | **Case Study** | **Same map** | | **Different map (Regions)** |
|---|---|---|---|---|
| | | **Same region** | **Different region** | |
| 1 | Case Study I | | ✓ | ✓ |
| 2 | Case Study II | ✓ | | |
| 3 | Case Study III | | ✓ | |
| 4 | Case Study IV | | | ✓ |

*Table 6.4 Selection of training images region (data) and testing images region (data) for different case studies*

| Sr. No. | Case Study | Training Images | | Testing Images | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 53C7 | 53F6 | 53C7 | 53F6 | 53F7 | 53F11 | 53K1 |
| 1 | Case Study I | 25 | 25 | 5 | 5 | 5 | 5 | 5 |
| 2 | Case Study II | 15 | 10 | 15 | 10 | - | - | - |
| 3 | Case Study III | 25 | - | 5 | - | - | - | - |
| 4 | Case Study IV | 10 | - | - | - | 3 | - | 2 |

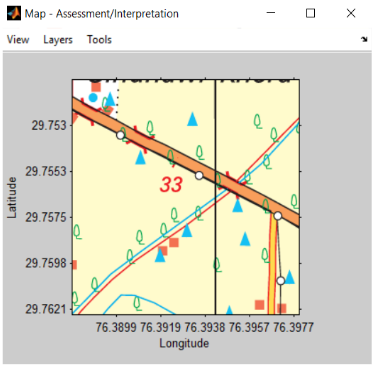
## 6.4 CASE STUDY I

In this case study, automatic map understanding carried out by MUS has been discussed for the different output of MUS viz., map interpretation, thematic layers of information, geolocation based layer data set. The MUS have been trained using training samples from OSM topographic maps, namely 53C7 and 53F6. The total 25 map regions from both of map sheets have been selected for training. These map regions are selected randomly. However, the system has been tested on five test regions, selected randomly from each of 53C7 and 53F6. These regions are sufficiently different from those regions, which have been selected for the training the system. In addition, the system has also been tested on rest of three topographic maps, which are not used for training MUS. The five test regions from each of OSM 53F7, 53F11, 53F6 topographic maps have been selected to test the performance of system unseen map images, which has been shown in Table 6.3. The map five map samples from each of the five map named as 53C7one to 53C7five, 53F6one to 53F6five, 53F7one to 53F7five, 53F11one to 53F11five, 53K1one to 53K1five of size 256 by 256 pixels have been selected from a topographic map, namely data sheet no. 53C7, 53F6, 53F7, 53F11, 53K1 respectively and given as an input to MUS. The map objects/symbols present in sample test map images have been understood and interpreted by MUS (as in Figure 6.7b). The MU handler generates map analysis report and stores in text file format. The MU handler instantiates the module, which scans and compares the metadata provided by Survey of India. Also, the system generated map analysis report file for the map object instances present at the same location coordinates (either x-y or geo-coordinates). The comparison consists of a number of map object instances present in referenced data and recognized by MUS at the same location as that of present in referenced data file. In addition to mapping object/symbol understanding, MUS also generates thematic information about maps in layers. It stores obtained a layer of information in .tiff format as well as in an excel spreadsheet. The MUS generates geo-location based map and layer dataset.

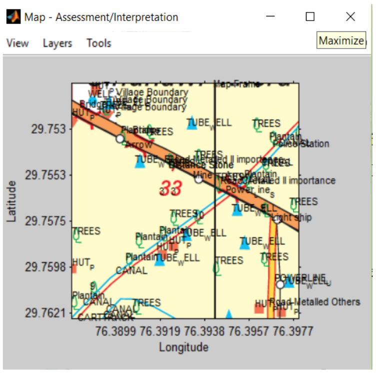
### 6.4.1 Map Symbol Understanding

A comparison of the number of instances of map objects in the reference (actual map) data and that in the interpreted map (i-map) generated by MUS has been carried out by ITMUS inbuilt accuracy assessment module. Few snapshots containing annotated maps and utility for map accuracy assessment have been provided in Figure 6.7 to Figure 6.9. In the case study I, accuracy assessment has been performed for 25 test images of size 256 by 256 pixels which have been selected from five GeoTIFF topographic maps. The results obtained on these test map images are encouraged. The majority of the failures has been observed from the fact that system has further scope for training at high density and object variability (due to distortion or occlusion) present in the topographic map.

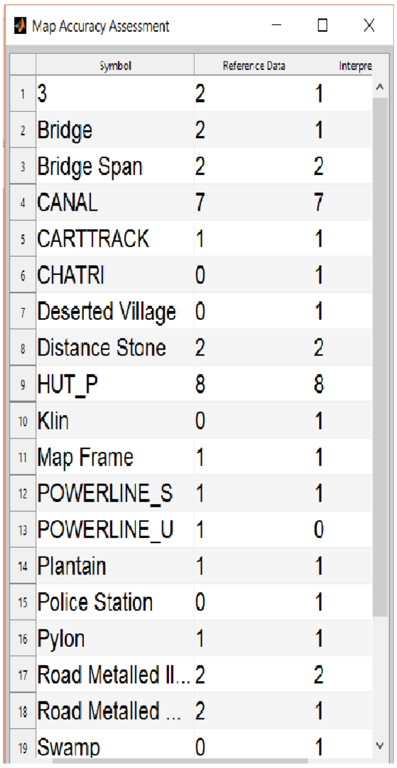
Thus, MUS has been trained and tested on Indian topographic maps. The data sheet numbers, territory name and other details have been already provided as in Table 6.1. The data selection criteria have been specified in Table 6.3. As said earlier, the sample map image data have been used as checking data.




a. Original map



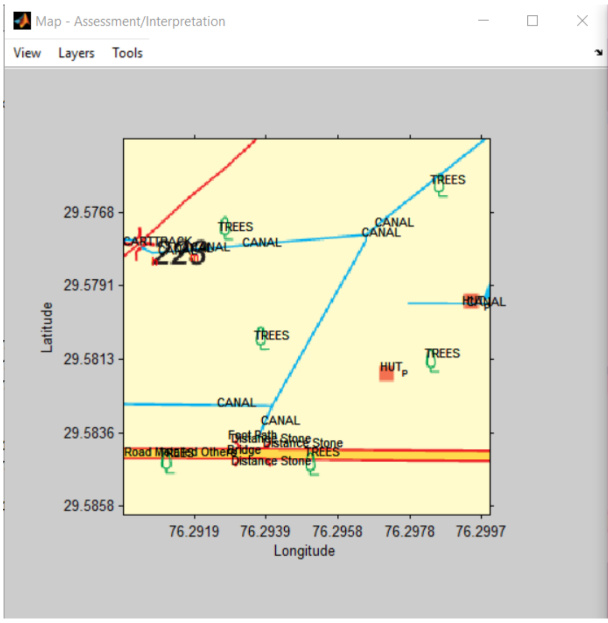

b. Interpreted map

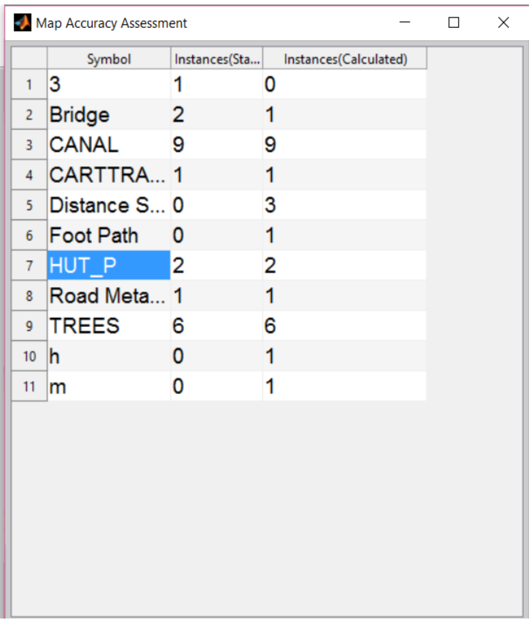

Map Accuracy Assessment

| | Symbol | Reference Data | Interpre |
|---|---|---|---|
| 1 | 3 | 2 | 1 |
| 2 | Bridge | 2 | 1 |
| 3 | Bridge Span | 2 | 2 |
| 4 | CANAL | 7 | 7 |
| 5 | CARTTRACK | 1 | 1 |
| 6 | CHATRI | 0 | 1 |
| 7 | Deserted Village | 0 | 1 |
| 8 | Distance Stone | 2 | 2 |
| 9 | HUT_P | 8 | 8 |
| 10 | Klin | 0 | 1 |
| 11 | Map Frame | 1 | 1 |
| 12 | POWERLINE_S | 1 | 1 |
| 13 | POWERLINE_U | 1 | 0 |
| 14 | Plantain | 1 | 1 |
| 15 | Police Station | 0 | 1 |
| 16 | Pylon | 1 | 1 |
| 17 | Road Metalled II... | 2 | 2 |
| 18 | Road Metalled ... | 2 | 1 |
| 19 | Swamp | 0 | 1 |

c. Comparison of number of instances of map objects in referenced data and interpreted data

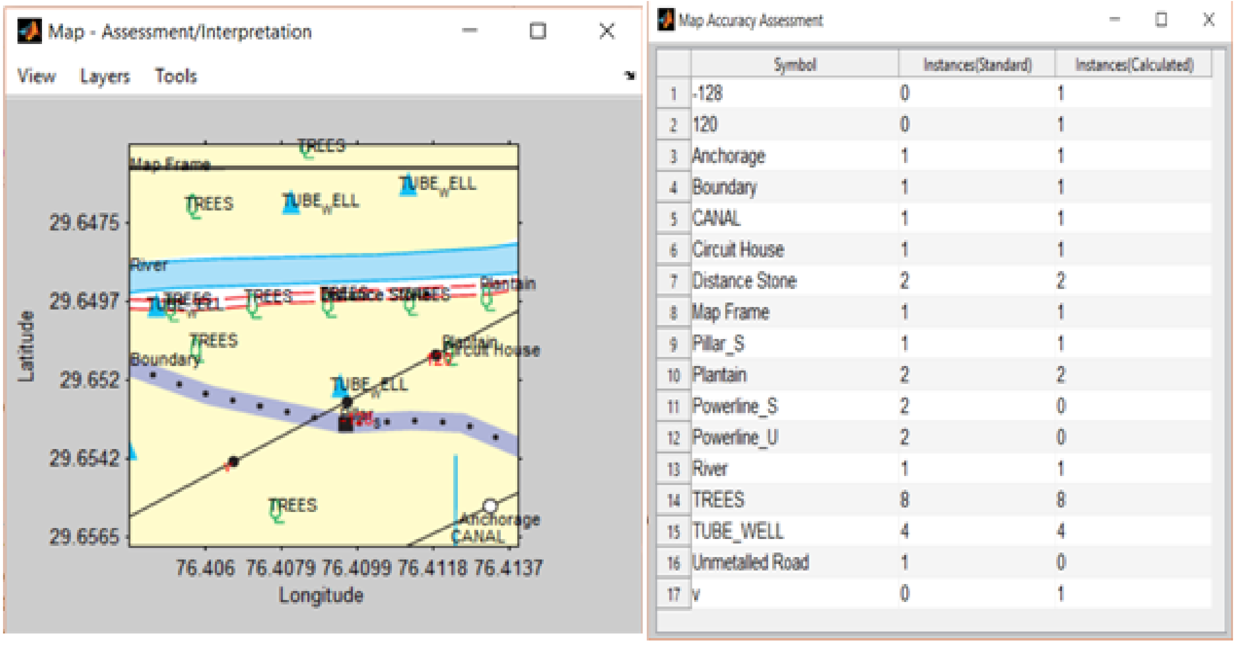
***Figure 6.7 Map understanding Output; (a) Original sample 53C7Fifth, (b) Interpreted map, (c) Comparision between number of instances in MUS interpreted map and reference map data of actual map***





Map Accuracy Assessment

| | Symbol | Instances(Sta... | Instances(Calculated) |
|---|---|---|---|
| 1 | 3 | 1 | 0 |
| 2 | Bridge | 2 | 1 |
| 3 | CANAL | 9 | 9 |
| 4 | CARTTRA... | 1 | 1 |
| 5 | Distance S... | 0 | 3 |
| 6 | Foot Path | 0 | 1 |
| 7 | HUT_P | 2 | 2 |
| 8 | Road Meta... | 1 | 1 |
| 9 | TREES | 6 | 6 |
| 10 | h | 0 | 1 |
| 11 | m | 0 | 1 |

***Figure 6.8 Map understanding (sample 53C7one) symbol understanding assessment***




| | Symbol | Instances(Standard) | Instances(Calculated) |
|---|---|---|---|
| 1 | -128 | 0 | 1 |
| 2 | 120 | 0 | 1 |
| 3 | Anchorage | 1 | 1 |
| 4 | Boundary | 1 | 1 |
| 5 | CANAL | 1 | 1 |
| 6 | Circuit House | 1 | 1 |
| 7 | Distance Stone | 2 | 2 |
| 8 | Map Frame | 1 | 1 |
| 9 | Pillar_S | 1 | 1 |
| 10 | Plantain | 2 | 2 |
| 11 | Powerline_S | 2 | 0 |
| 12 | Powerline_U | 2 | 0 |
| 13 | River | 1 | 1 |
| 14 | TREES | 8 | 8 |
| 15 | TUBE_WELL | 4 | 4 |
| 16 | Unmetalled Road | 1 | 0 |
| 17 | v | 0 | 1 |

***Figure 6.9 Map Understanding (sample 53C7four) Symbol understanding assessment***

### 6.4.2 Thematic Layers of Information

The MUS gives the thematic geo-location based layers of information. Topographic map understanding system, also able to analyze map from much perceptive. For example, map analysis in the form of constituent thematic layers. Map layer consists of many objects of the same category. The building category has been instantiated into a residential building, religious building, and other buildings. The MUS successfully understands the instances and assign their semantics to respective map objects. The ITMUS enables to group the map objects from different color layers, but having a common intermediate description. From Figure 6.10 (f) -(k), it has been clear that system recognizes the group of the objects semantically. For example, temple, mosques have also been recognized as a religious building. The metalled road, cart track has also been recognized as communication object. The understanding result of topographic map samples 53C7RS (RS-random selection) and 53C7fifth have been shown in Figure 6.10 and Figure 6.11 respectively. The MUS generated layers of information for randomly chosen and 53C7five samples have been shown in Figure 6.10 (b) to 6.10 (k) and 6.11 (a) to 6.11 (i) respectively. To perform the map layer extraction, assessment module provides a framework for loading ITMUS generated color layers of topographic maps. Next, ground truth layer data for the same area which has been prepared by manual delineation and converted into a binary mask. Further, overlaying between the system and ground truth layer has been done. The overlaying between these two layers shows the extent of objects extracted or missed in ITMUS layer. For this experiment, cost or penalty matrix has been determined by domain values of low, medium and high. It has been given in detail in Appendix II. In Figure 6.12, snapshots have been given, in which left-hand side is system extracted layer, in the middle is layer created by manual delineation and at right-hand side is overlaying of previous two layers. The overlaid i.e. operation of binary and shows that misclassification cost (as discussed in section 3.6) has been low for all layers.

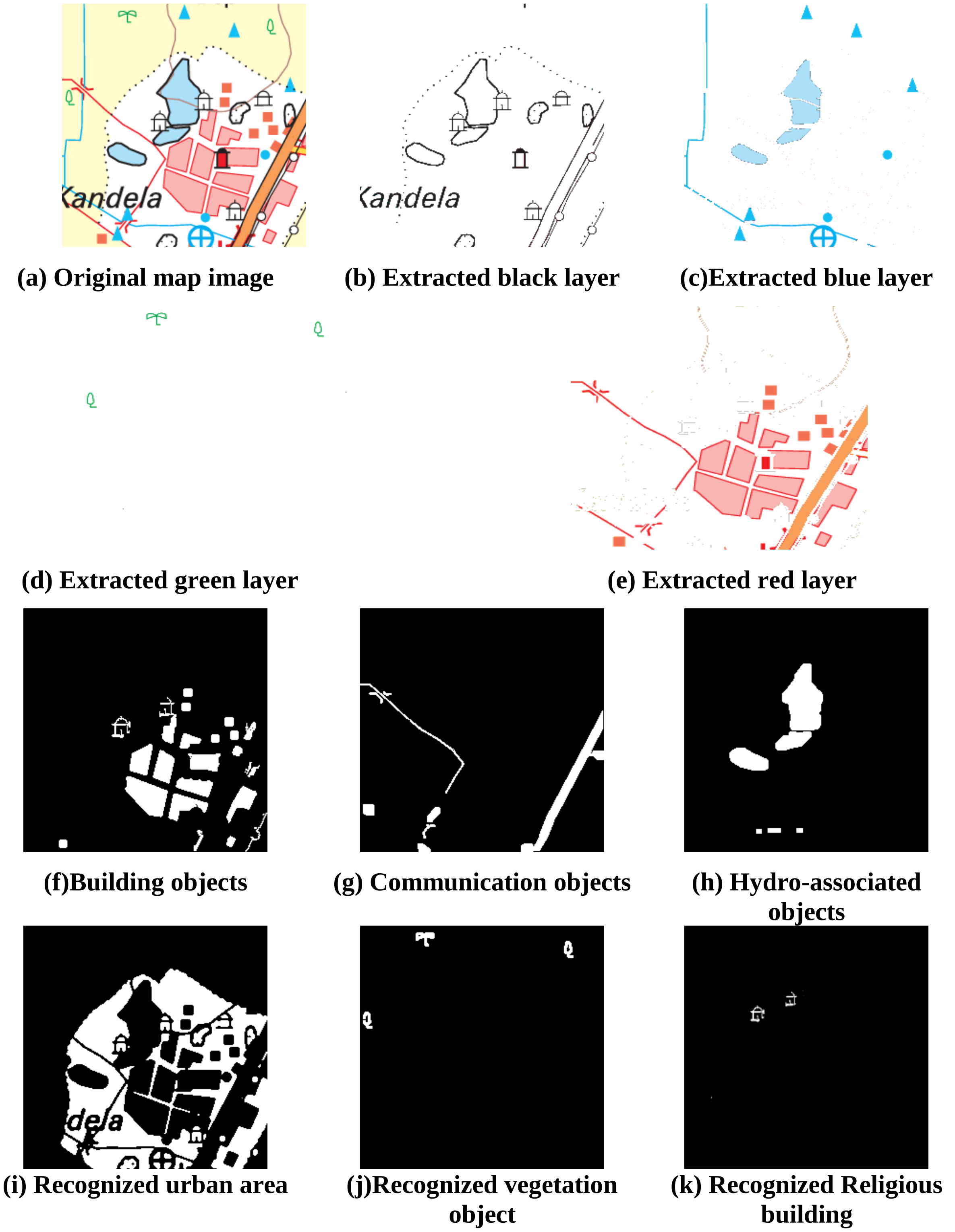
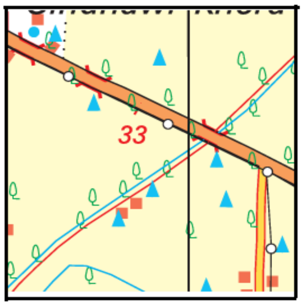
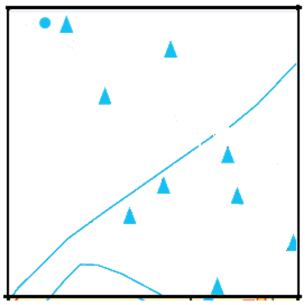


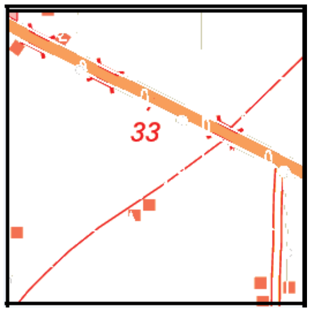

*Figure 6.10 (a) Original topographic map image from 53C7, (b)Extracted black layer, (c)Extracted blue layer, (d) Extracted green layer, (e) Extracted red layer, (f) Recognized Building object, (g) Recognized road object , (h) Recognized Hydro-associated objects, (i) Recognized urban area, (j) Recognized vegetation object, (k) Recognized Religious building object*



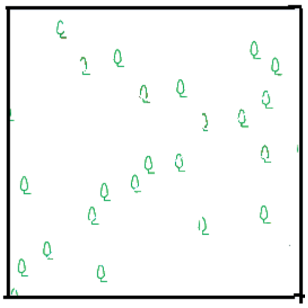

**(a) Original topographic map sample-53C7fifth**



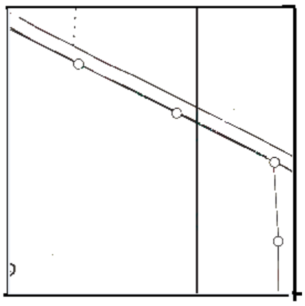
**(b) Hydrography object**



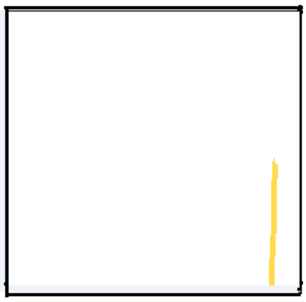

**(c) Man-made object**



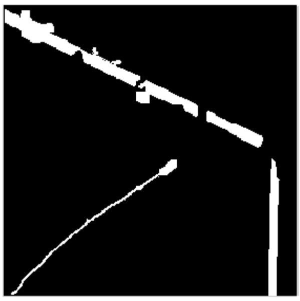
**(d) Vegetation Layer**



**(e) Utility layer**



**(f) Basic communication layer**



**(i) Road Layer**


**(g) Building Layer (binary)**


**(h) Text Layer**

***Figure 6.11 Thematic layers of information generated by ITMUS; (a) Original topographic map sample-53C7fifth, (b) Hydrography layer, (c)Man-made object layer, (d) Vegetation Layer, (e) Utility layer, (f) Basic communication layer, (g) Building Layer (binary), (h) Text Layer, (i) Road Layer***

### 6.4.3 Geo-Location Based Layer Data Set

MUS also generate the geo-location based spatial data set for recognizing semantic layers. This dataset consists of system predicted semantic meaning/interpretation of the map object along with geolocation at which it has been found (latitude-longitude location). MUS also stores shape and structural properties of the map object. The sample dataset, which has been generated for man-made objects by MUS are shown below in Figure 6.13.

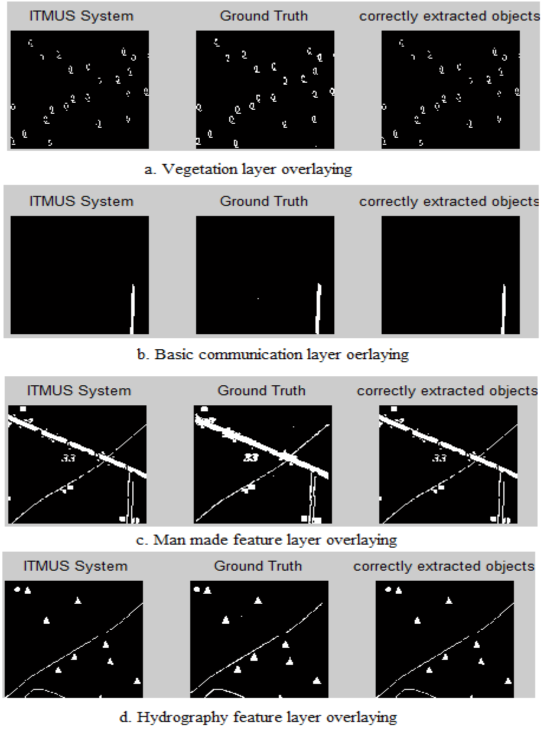



***Figure 6.12 Manual delineation and system extracted object overlaying***

### 6.4.4 MUS Performance Evaluation

The possibility of building an intelligent system to understand topographic map automatically has become reality. The performances of the developed system and the human interpretation have been compared. That means, the results of the understanding system have been evaluated according to the rules applied for evaluation of human understanding [190]. The evaluation has been achieved by comparison between the automatic map symbol understanding result and the reference data which has been created by Survey of India (SOI). The number of instances present in the actual test map and number of MUS interpreted instances for various types of map objects has been reported in Table 6.5. The color legends have been provided at the bottom of Table 6.5 which defines four categories of outcomes (TP, FP, FN, FP U FN) represented by a unique color for better understanding. As given in section 3.6, the result of the MUS has been compared with the reference data. The reference data have been created by a human operator at SOI. Two global quality measures - completeness and correctness have been used for evaluating the results. The completeness means the percentage of the reference data (REF) and determined based on automatically extracted data, while the percentage of correctly extracted objects (EXT) is represented by correctness. The parameters considered in determining these measures: TP (True Positive), FP (False Positive), and FN (False Negative) defined as follows:

TP: All instances of map objects (T) common in both data sets REF and EXT. This number shows correctly interpreted objects;

FP: All instances of map objects (P), which are members of the data set EXT but not included in REF. It shows number of false interpretations;

FN: All instances of map objects (N), which are members of the data set REF but not included in EXT. It gives the number of map objects which are not interpreted either correctly or wrongly.

| 1 | Symbol | Latitude | Longitude | branches | endpts | euler no | shape | solidity | orientation | height | width |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | Village/Town | 29.7535 | 76.3896 | 0 | 2 | 1 | 2 | 0.9655 | -18.5245 | 6.0001 | 4 |
| 3 | Road Metal... | 29.7457 | 76.3932 | 1 | 3 | 1 | 3 | 0.9026 | -26.9752 | 24 | 3.0000 |
| 4 | Road Metal... | 29.7483 | 76.3924 | 0 | 2 | 1 | 4 | 0.8799 | -26.3222 | 25.4000 | 4.2000 |
| 5 | Road Metal... | 29.7534 | 76.3898 | 1 | 3 | 1 | 3 | 0.7758 | -26.7436 | 58.2852 | 3.1727 |
| 6 | Oblonged ... | 29.7522 | 76.3898 | 1 | 1 | 1 | 2 | 1 | 0 | 4 | 0 |
| 7 | Oblonged ... | 29.7522 | 76.3896 | 0 | 2 | 1 | 2 | 1 | 0 | 10 | 2 |
| 8 | HUT_P | 29.7533 | 76.3967 | 0 | 2 | 1 | 2 | 1 | 90 | 9 | 8 |
| 9 | HUT_P | 29.7439 | 76.3990 | 0 | 2 | 1 | 2 | 1 | 0 | 9 | 8 |
| 10 | HUT_P | 29.7440 | 76.3984 | 0 | 1 | 1 | 2 | 1 | 0 | 9 | 9 |
| 11 | HUT_P | 29.7483 | 76.3958 | 0 | 1 | 1 | 2 | 1 | -45.0000 | 9.0001 | 9 |
| 12 | HUT_P | 29.7534 | 76.3907 | 0 | 2 | 1 | 3 | 0.9444 | 68.3764 | 8.5714 | 7.1429 |
| 13 | HUT_P | 29.7489 | 76.3960 | 0 | 2 | 1 | 4 | 0.8636 | -52.4551 | 12.2500 | 11 |
| 14 | HUT_P | 29.7429 | 76.3985 | 2 | 2 | 0 | 4 | 0.8923 | -80.8437 | 12 | 10 |
| 15 | HUT_P | 29.7518 | 76.3904 | 15 | 3 | -7 | 2 | 0.8830 | 18.7786 | 15.0000 | 12 |
| 16 | Distance St... | 29.7483 | 76.3926 | 0 | 2 | 1 | 2 | 0.9756 | -80.4673 | 9.0001 | 8 |
| 17 | Distance St... | 29.7483 | 76.3926 | 0 | 2 | 1 | 2 | 0.9756 | -80.4673 | 9.0001 | 8 |
| 18 | Arrow | 29.7431 | 76.3917 | 0 | 2 | 1 | 3 | 0.6316 | 43.1348 | 18 | 5.9380 |
| 19 | 2 | 29.7482 | 76.3937 | 1 | 3 | 1 | 2 | 0.5930 | 73.5012 | 16.0001 | 10.4444 |
| 20 | 3 | 29.7488 | 76.3937 | 1 | 3 | 1 | 2 | 0.5920 | 75.4689 | 16 | 11 |
| 21 | Bridge | 29.7501 | 76.3911 | 8 | 2 | -3 | 3 | 0.5253 | -27.4671 | 12.7745 | 6.1615 |
| 22 | Deserted Vi... | 29.7528 | 76.3901 | 9 | 3 | -3 | 3 | 0.5263 | -26.9910 | 12.8466 | 2.8434 |
| 23 | Bridge Span | 29.7505 | 76.3917 | 24 | 2 | -11 | 2 | 0.5182 | -28.2861 | 9.7151 | 24 |
| 24 | Bridge Span | 29.7455 | 76.3930 | 30 | 4 | -13 | 3 | 0.4654 | -19.9486 | 15.4789 | 22.6382 |
| 25 | CARTTRACK | 29.7532 | 76.3992 | 3 | 5 | 1 | 3 | 0.2812 | 38.7269 | 103.4963 | 5.1086 |
| 26 | Bridge Span | 29.7423 | 76.3941 | 30 | 4 | -13 | 3 | 0.4654 | -19.9486 | 15.4789 | 22.6382 |

***Figure 6.13 Man-made object dataset***

The truly recognized map objects have been measured for each test map group. The addition of all correctly recognized map objects is designated as TP. For example, sample group, namely as 53C7one~five, have been tested on ITMUS and found that 193 map objects are recognized correctly. It has been validated by referring the metadata created by SOI. Like this, 387, 219, 355 and 287 True positive map objects have been measured from 53F6one~five, 53F7one~five, 53F11one~five, 53K1one~five respectively. In the same manner, measuring actual interpretation and referring metadata, FN and FP have been measured in the corresponding test map groups as above.

$$TP = \sum_{T=1,i=1}^{T=5,i=1} Test\ map\, T_i \qquad FN = \sum_{N=1,i=1}^{N=5,i=1} Test\ map\, N_i$$

= 193+387+219+255+228;

=1282

= 12+29+7+20+16=84

$$FP = \sum_{P=1,i=1}^{P=5,i=1} Test\ map\ P_i$$

$$= 11$$

***Table 6.5 The list of all map symbols those occurred in 25 samples from 5 OSM topographic map and the number of instances interpreted by MUS (EXT) as well as the number of instances present in actual map***

| Sr. No. | Map Symbols | Data sheet number of territories | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 53C7one~five | | 53F6one~five | | 53F7one~five | | 53F11one~five | | 53K1one~five | |
| | | ITMUS result (EXT) | Data By SOI (REF) | ITMUS result (EXT) | Data By SOI (REF) | ITMUS result (EXT) | Data By SOI (REF) | ITMUS result (EXT) | Data By SOI (REF) | ITMUS result (EXT) | Data By SOI (REF) |
| 1 | Trees | 57 | 63 | 20 | 21 | 34 | 35 | 20 | 22 | 33 | 36 |
| 2 | Palms | 0 | 0 | 3 | 4 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | Surveyed Tree | 0 | 0 | 1 | 2 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | Forest Riband | 0 | 0 | 7 | 9 | 3 | 4 | 1 | 2 | 0 | 2 |
| 5 | Hut_p | 20 | 20 | 107 | 107 | 34 | 34 | 101 | 101 | 54 | 54 |
| 6 | Village/Town | 57 | 58 | 15 | 15 | 26 | 28 | 31 | 31 | 57 | 62 |
| 7 | Pack-track | 0 | 0 | 5 | 4 | 3 | 1 | 0 | 0 | 3 | 0 |
| 8 | Foot path | 0 | 0 | 4 | 4 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | Village boundary | 1 | 1 | 5 | 5 | 8 | 8 | 7 | 7 | 7 | 7 |
| 10 | Contour | 0 | 0 | 159 | 169 | 49 | 49 | 30 | 30 | 3 | 3 |
| 11 | Dry stream | 0 | 0 | 15 | 18 | 7 | 7 | 2 | 5 | 0 | 3 |
| 12 | Powerline_S | 1 | 1 | 6 | 6 | 0 | 0 | 5 | 7 | 4 | 4 |
| 13 | Unmetalled Road | 1 | 1 | 3 | 5 | 0 | 0 | 0 | 0 | 3 | 6 |
| 14 | Scrub | 0 | 0 | 2 | 3 | 5 | 7 | 3 | 3 | 5 | 8 |
| 15 | Triangulated height | 0 | 0 | 2 | 3 | 0 | 0 | 1 | 0 | 0 | 0 |
| 16 | Bridge | 5 | 8 | 3 | 5 | 2 | 2 | 3 | 4 | 3 | 4 |
| 17 | Road metalled II importance | 2 | 2 | 2 | 2 | 0 | 0 | 2 | 2 | 2 | 2 |
| 18 | Canal | 1 | 1 | 3 | 3 | 1 | 1 | 4 | 4 | 4 | 4 |
| 19 | River | 1 | 1 | 0 | 1 | 0 | 0 | 2 | 2 | 1 | 1 |
| 20 | Dry wet land | 0 | 0 | 3 | 3 | 7 | 7 | 4 | 4 | 8 | 8 |
| 21 | Boundary | 1 | 1 | 2 | 2 | 2 | 2 | 1 | 1 | 0 | 0 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 22 | Temple | 6 | 8 | 6 | 8 | 8 | 9 | 4 | 9 | 3 | 3 |
| 23 | Grass | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 24 | Road Metalled others | 4 | 4 | 7 | 7 | 4 | 4 | 11 | 11 | 14 | 14 |
| 25 | Distance stone | 2 | 1 | 1 | 2 | 1 | 1 | 2 | 2 | 7 | 11 |
| 26 | Overhead Tank | 0 | 0 | 1 | 1 | 0 | 0 | 2 | 2 | 0 | 0 |
| 27 | Mosque | 2 | 2 | 1 | 2 | 3 | 3 | 1 | 2 | 0 | 0 |
| 28 | Chatri | 0 | 0 | 2 | 2 | 1 | 1 | 0 | 0 | 1 | 1 |
| 29 | Grave | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 |
| 30 | Spring | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| 32 | Tube well | 20 | 20 | 0 | 0 | 10 | 10 | 6 | 6 | 2 | 2 |
| 33 | Cart track | 4 | 4 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 34 | Piller_S | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 35 | Fort | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 37 | Tank_P | 2 | 2 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 |
| 38 | Post Office | 2 | 2 | 0 | 0 | 2 | 0 | 0 | 1 | 1 | 1 |
| 39 | Well | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| 40 | Powerline_U | 1 | 1 | 0 | 1 | 1 | 3 | 2 | 4 | 2 | 3 |
| 41 | Map Grid | 1 | 1 | 0 | 0 | 0 | 0 | 2 | 2 | 3 | 3 |
| 42 | Hospital | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 |
| 43 | Police station | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 |
| 44 | Dry Tank | 0 | 0 | 0 | 0 | 2 | 2 | 1 | 1 | 7 | 7 |
| 45 | Rest House | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| 46 | Embankment | 0 | 0 | 0 | 0 | 1 | 1 | 4 | 5 | 0 | 0 |
| 47 | Plantain | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 2 | 1 |
| 48 | Broken ground | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| | Interpreted object | 193 | 205 | 387 | 416 | 219 | 226 | 255 | 275 | 228 | 254 |
| | % of correct Interpretation | 94.14 | | 95.43 | | 96.90 | | 92.72 | | 89.76 | |

(TP) (FP)

(FP U FN) (FN)

The quality measures like overall completeness, overall correctness and rate of correct recognition have been calculated as given in [71, 170, 203, 351]. The result has been obtained for 25 regions of size 256X256 pixels which had been selected from 5 OSM Geotiff topographic maps (namely 53C7, 53F6, 53F7, 53F11, 53K1). All the images of testing regions have completely distinct from that of training regions. The number of map objects recognized and interpreted by MUS (EXT) and the actual number of map objects present in the same region (REF) has been reported in Table 6.5. From the observations and results summarized in Table 6.5, the quality measures like overall completeness, overall correctness, and rate of correct recognition have been deduced by the equations 3.13, 3.14 and 3.15 respectively. The range of domain for overall completeness and correctness is 0 to 1. If a value has been approaching towards or close to 1 then the performance of the system in terms of completeness and correctness will be very good. The values may be represented in percentage also. The quality measures and obtained values have been summarized in Table 6.6.

***Table 6.6 Quality Measures***

| | Overall Completeness [0, 1] | Overall Correctness [0, 1] | Rate of Correct Recognition (%) |
|---|---|---|---|
| 53C7<br>53F6<br>53F7<br>53F11<br>53K1 | 0.93 | 0.99 | 93.79 |

**Quantitative and Qualitative result analysis on noisy map objects**

In this study, standard OSM Topographic maps have been used. The OSM data get prepared and distributed in the standard georeferenced form by Survey of India. Therefore, it never contains any noisy data. Hence, no noisy data has been tested in this study. However, topographic maps are dense, crowded and highly complex. So, the noisy data in these maps corresponds to the map objects whose appearance is not completely visible or certain i.e., the uncertainty / noise of map objects due to their partial appearance, intersection or overlapping conditions. The performance of ITMUS has also been assessed for partial appearance, intersection or overlapping of different map objects. In order to conduct the analysis for these kinds of noisy objects present in OSMs, five sample regions have been considered as shown in Figure 6.14 a, Figure 6.14 c, Figure 6.14 e, Figure 6.14 g, and Figure 6.14 i. The samples images have interpreted by ITMUS and also, been visually interpreted. The corresponding Figures as interpreted by ITMUS are Figure 6.14 b, Figure 6.14 d, Figure 6.14 f, Figure 6.14 h, and Figure 6.14 j respectively. In order to carry out quantitative analysis, number of corresponding map symbols which are partial, intersected or overlapped in both the outputs have been counted. It has been found that out of the 16 partially visible/present map symbols 12 symbols have been recognized correctly by ITMUS. Further, out of 82 intersected map symbols, 62 have been recognized correctly and out of 29 overlapped map symbols, 24 have been recognized correctly by the ITMUS. The detail break up corresponding to different types of noisy symbols present in the sample images and those in interpreted is given in Table 6.7.

Based on this testing, it has been clear that ITMUS interprets 75 % of partial objects. The partial object interpretation can be improved further. ITMUS interprets more that 75% of intersected objects. The condition of intersection of linear objects can be further processed to improve the interpretation result. The ITMUS interprets about 82% of overlapped map symbols correctly, which is very promising. Thus, the system has been tested to assess the performance in the presence of uncertainty which may be due to partial appearance, intersection or overlapping with other map objects. The quantitative result has been summarized in Table 6.7.

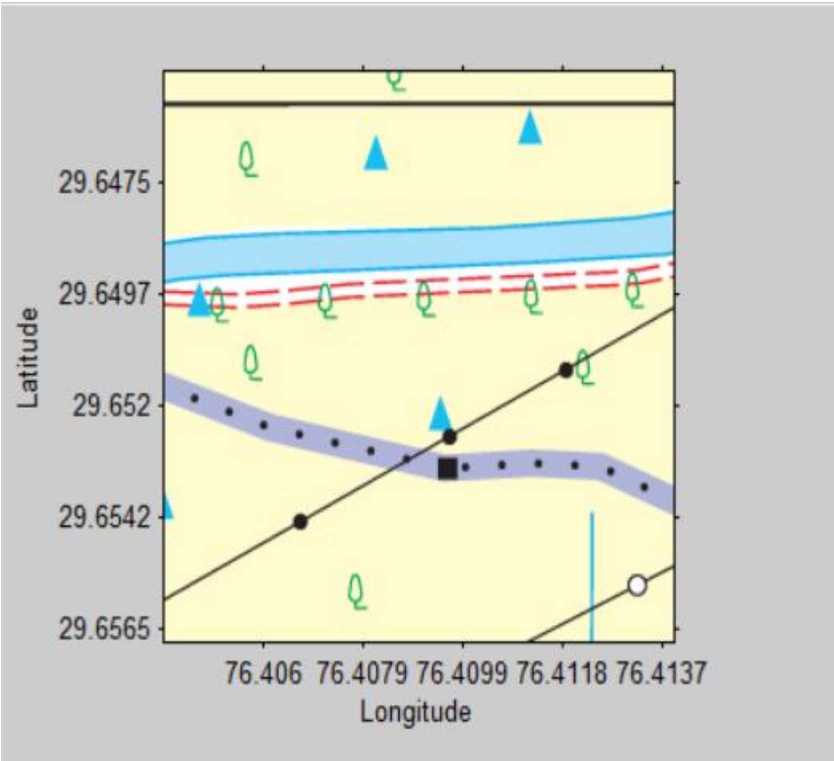



***Figure 6.14(a). OSM 53C7- Sample 1***

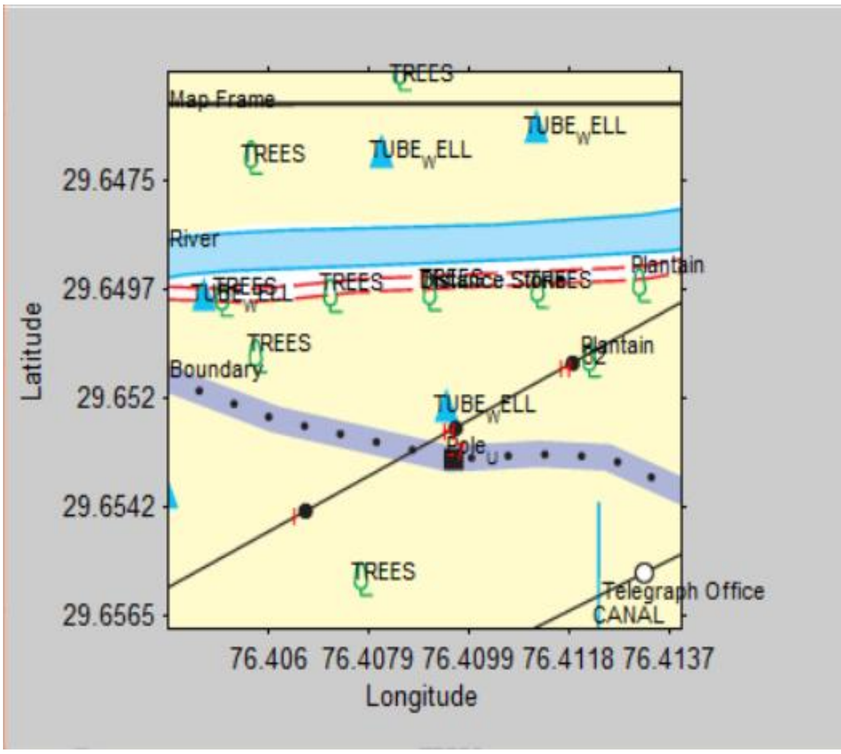



*Figure 6.14 (b). ITMUS Interpretation of sample in Figure 6.14 (a)*

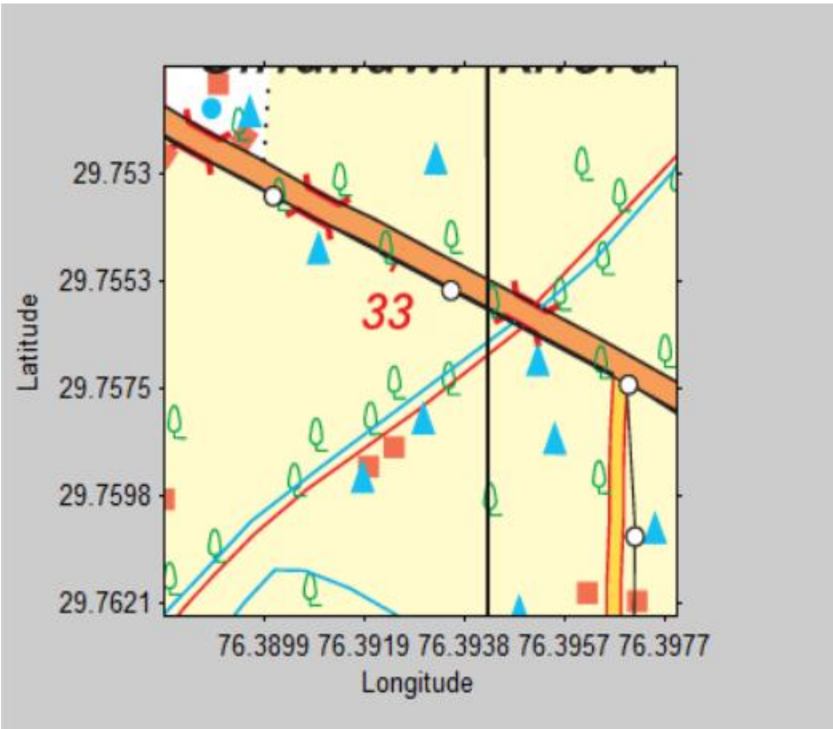



*Figure 6.14 (c). OSM 53C7 - Sample 2*

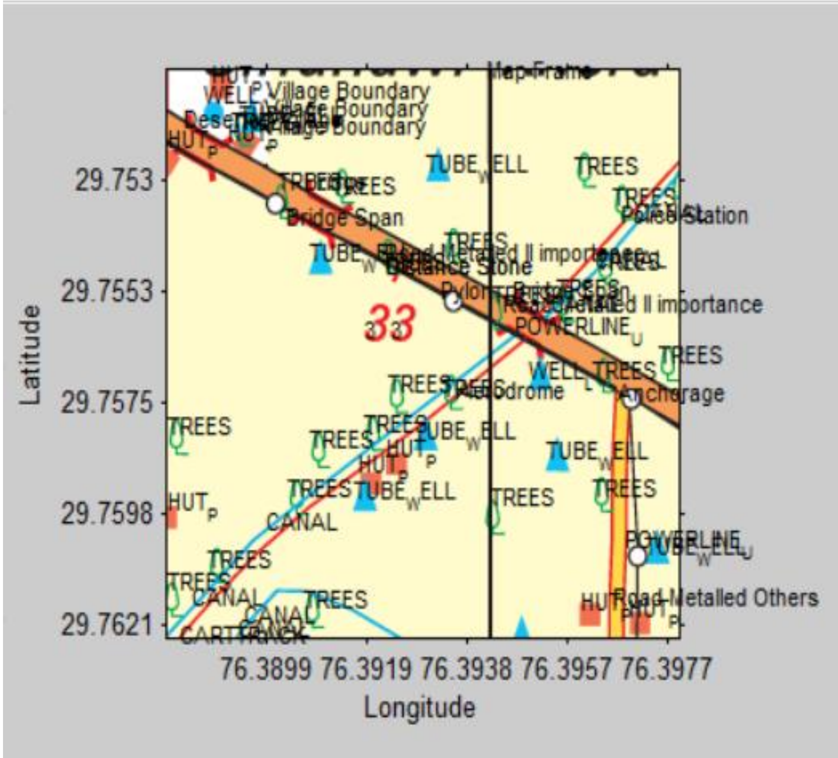



*Figure 6.14 (d). ITMUS Interpretation of sample in Figure 6.14 (c)*

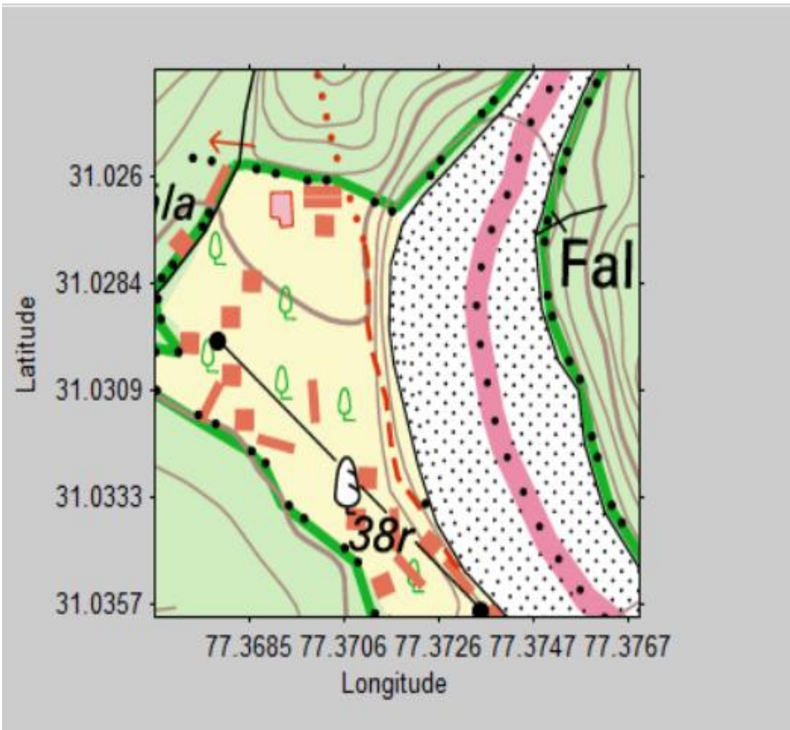



*Figure 6.14 (e). OSM 53F6 - Sample 1*

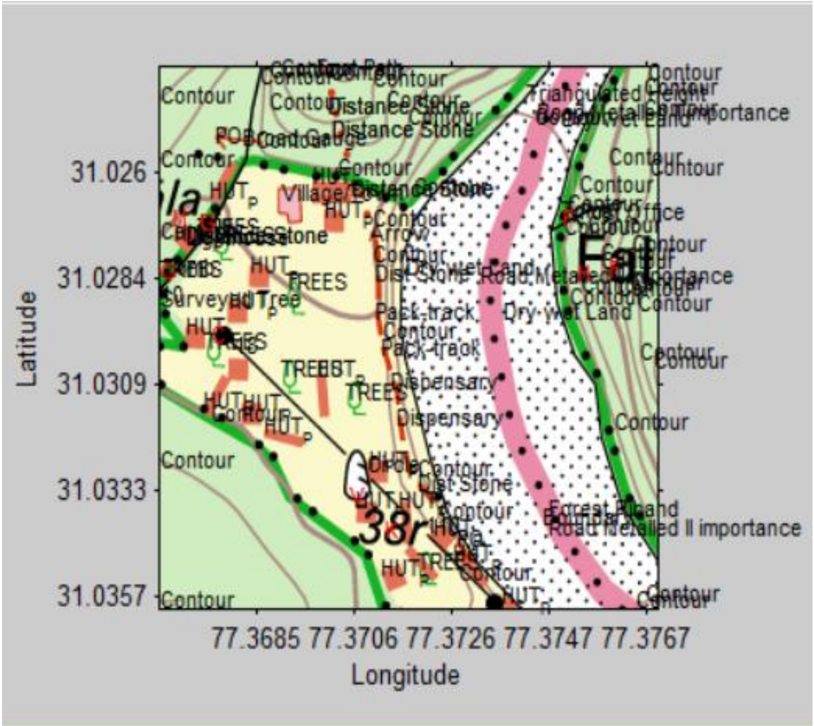



*Figure 6.14 (f). ITMUS Interpretation of sample in Figure 6.14 (e)*

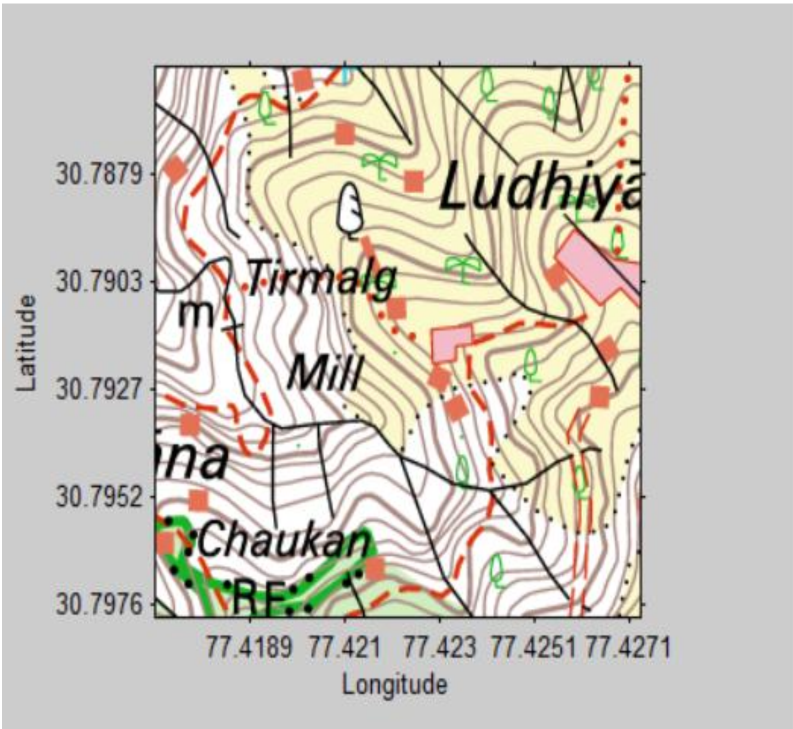



*Figure 6.14 (g). OSM 53F6 - Sample 2*

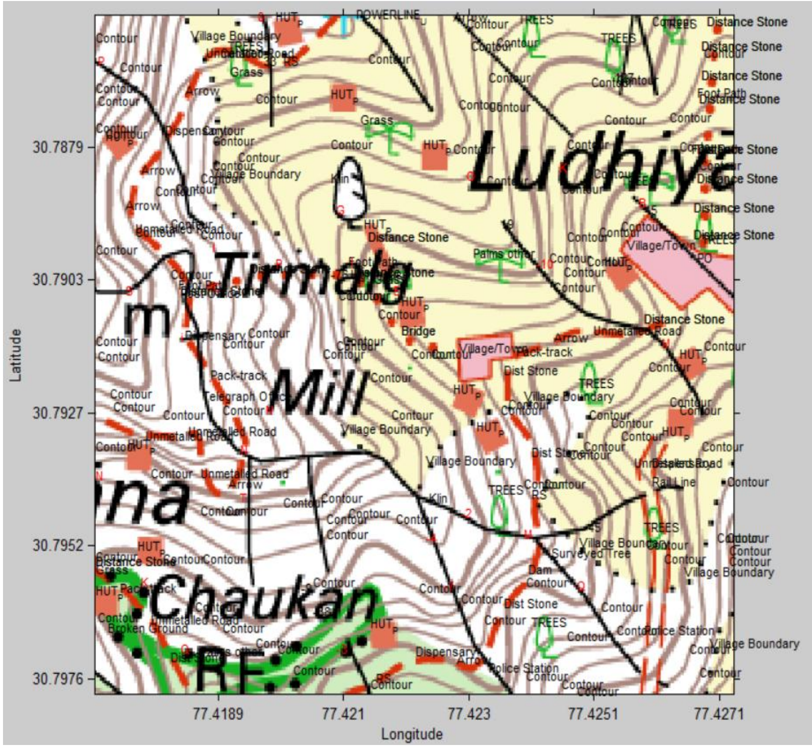



*Figure 6.14 (h) ITMUS Interpretation of sample in Figure 6.14 (g)*

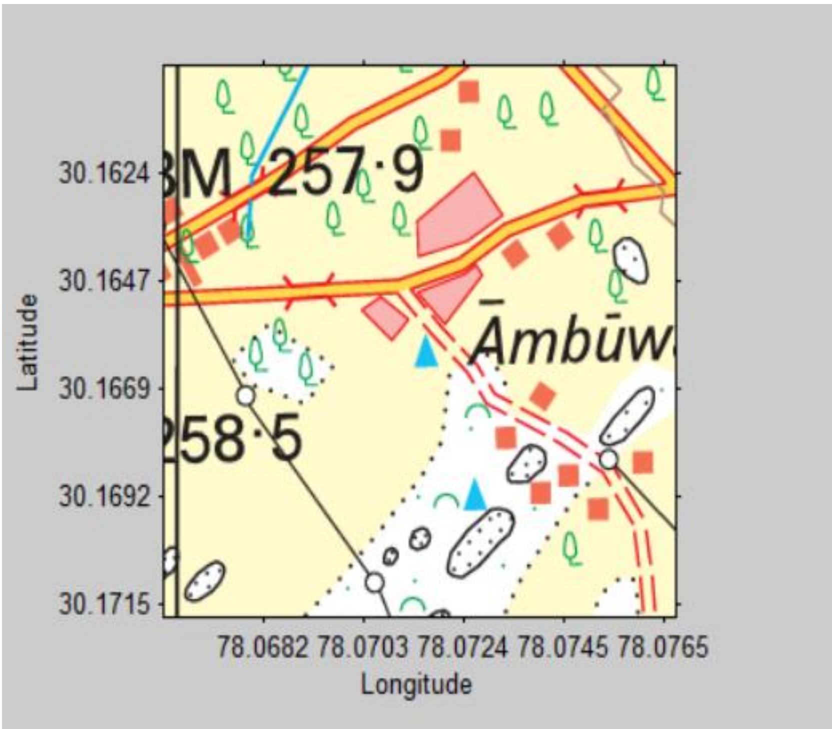



*Figure 6.14(i). OSM 53K1 - Sample 1*

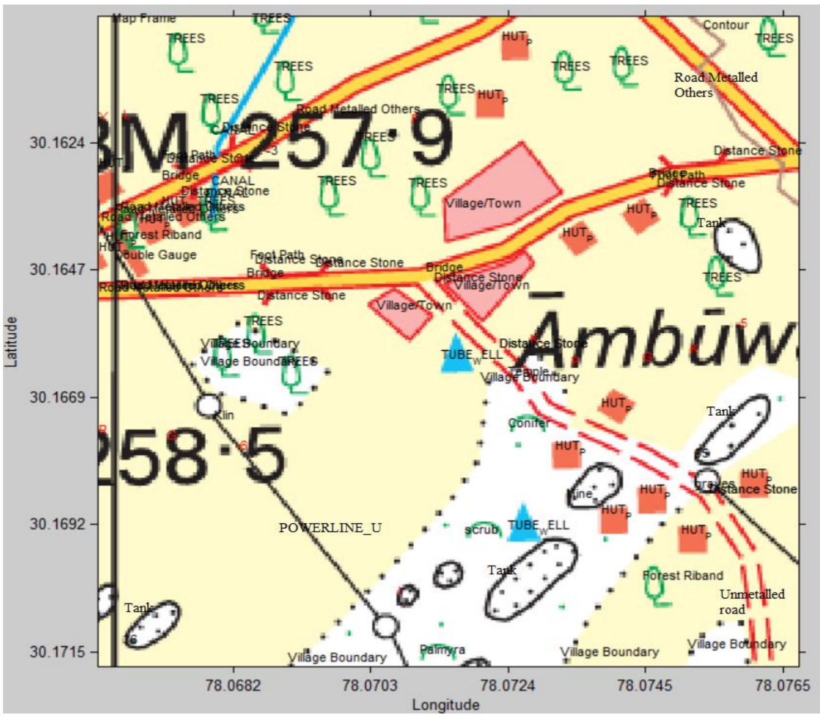



*Figure 6.14 j. ITMUS Interpretation of sample in Figure 6.14 (i)*

*Table 6.7 Quantitative result for noisy symbols*

| Noisy objects in Sample regions which are | Output | Sample region 1 | Sample region 2 | Sample region 3 | Sample region 4 | Sample region 5 |
|---|---|---|---|---|---|---|
| Partial (Present) | | 2 | 5 | 1 | 4 | 4 |
| | Interpreted/ Recognized | 1 | 5 | 1 | 3 | 2 |
| Intersected (Present) | | 8 | 13 | 3 | 43 | 15 |
| | Interpreted/ Recognized | 7 | 11 | 1 | 35 | 10 |
| Overlapped (Present) | | 1 | 4 | 5 | 13 | 6 |
| | Interpreted/ Recognized | 1 | 4 | 5 | 10 | 4 |

This quantitative result has been provided in Table 6.7. The qualitative analysis is mainly based on the quality or extent of extraction of map objects that has been identified by observations only. The two sample map regions (Figure 6.15 a and Figure 6.16 a.) have been considered to carry out qualitative analysis. ITMUS identifies and recognizes all partial/intersected trees (Figure 6.15 c). The vegetation objects which are partial or intersected are visually interpreted by performing manual delineation (Figure 6.15 d). The part of an object is so small that it cannot be delineated manually, but ITMUS correctly extracts it. Thus, partial objects which cannot be delineated manually is also recognized by ITMUS. Thus, ITMUS is more promising and error free as well. Qualitative analysis of map object extraction has been performed on interpretation of the OSM Sample region 4 (53C7). The extent of corresponding layer extraction from sample region 2 has been performed. ITMUS extracts most of the partial and intersected objects (in Figure 6.16 c -6.16 f.).

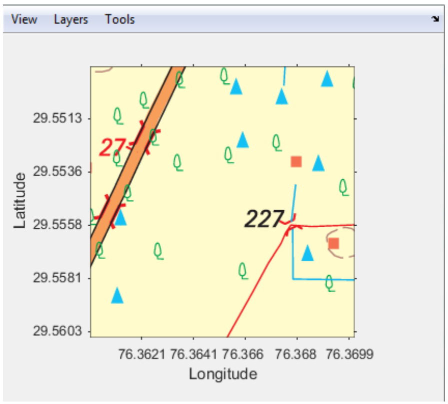



***Figure 6.15(a). OSM 53C7- Sample 3***

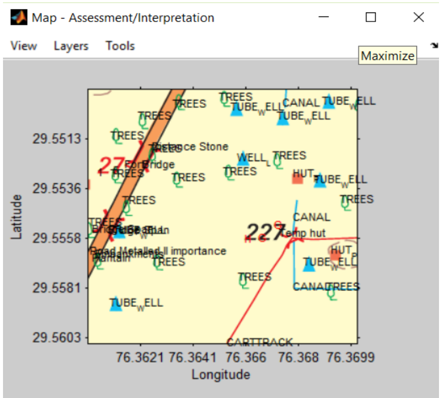



***Figure 6.15(b).ITMUS Interpretation of sample in Figure 6.15 (a)***

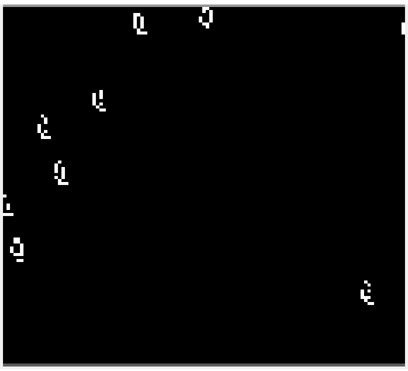


***Figure 6.15(c) ITMUS Interpretation of Intersected/Partial green objects of sample in Figure 6.15 (a)***

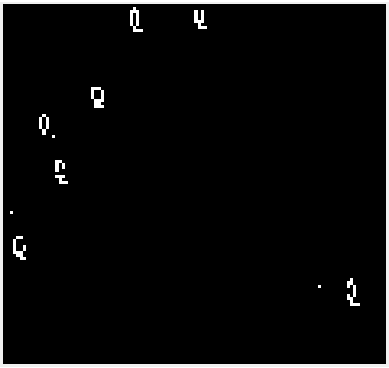


***Figure 6.15(d).Visual Interpretation of Intersected/Partial green objects of sample in Figure 6.15 (a)***

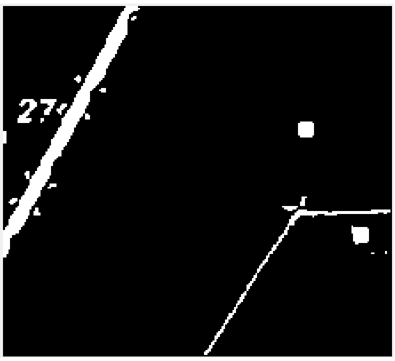


***Figure 6.15(e). ITMUS Interpretation of Intersected/Partial man made objects of sample in Figure 6.15 (a)***

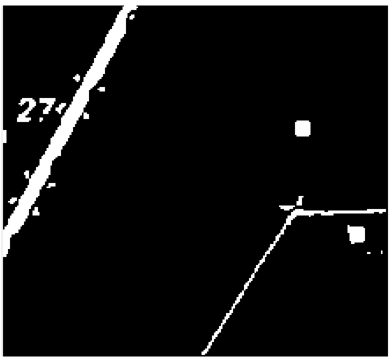


***Figure 6.15(f). Visual Interpretation of Intersected/Partial map made objects of sample in Figure 6.15 (a)***

ITMUS performs vegetation extraction as well as interpreted very little or partial appearance of the tree (vegetation) correctly (Figure 6.16 c). ITMUS extracts text (Figure 6.16 d), ITMUS identifies Hydrological objects (Figure 6.16 e). IMUS also extracts the most of the road network (Figure 6.16 f). Thus, the result obtained by ITMUS is qualitatively better.

## 6.5 CASE STUDY II

The developed system has been trained for 117 types of map objects by selecting total 25 random regions from OSM 53C7 and 53F6 Indian topographic map. In this case study, the system has been trained for total 25 random regions from OSM 53C7 (Figure 6.14 a) and 53F6 Indian topographic map. The 5 groups of the sample images have been formed for carrying out 5-fold cross validation (leave one sample out). Topographic images having sizes 256X256 pixels (from OSM 53C7 and 53F6) have been used for both training and testing. The system has been trained on sample regions (Figure 6.14 i.).Topographic images having sizes 256X256 pixels (from OSM 53C7 and 53F6) have been used for both training and testing. The topographic map datasets contain 4443 samples, which have been acquired from 25 regions selected randomly. The system has been trained on sample regions in an iterative manner. The data set acquired from the 25 sample regions has contained 4443 data samples, but these data sets may include a varying number of samples (instances) for each symbol. 5 groups of the sample images have been formed for carrying out 5-fold cross validation (leave one sample out). The researchers (Alvarez, S. A., [15], N. Ikonomakis, K.N. Plataniotis, M. Zervakis, and A.N. Venetsanopoulos [132], Ali Serhan Koyuncugil [172]) have demonstrated an important criterion which has been used for testing the efficiency of the search and retrieval using V-fold cross validation and same has been elaborated in section 3.6 The ITMUS has been trained on 4 sample regions sets and tested on 5$^{th}$ set. Thus, in every iteration, four sets have been used for training and one set has been used for testing. The process has been repeated till all the sample regions sets have been tested once. Thus, the map symbols found in the five sample regions sets have been interpreted by using trained models which show an overall success rate of 90.91%. Table 6.8 shows that Permanent Hut, tree, antiquities, Metalled road others and grass are having a higher recognition rate as compared to 16 other symbols of sample images. In other words, the errors in recognition for Hut, Tree and Antiquities are seen to be lower than other symbols. The percentages of correct recognitions achieved have also been drawn from 5 test images set of size 256 x 256 pixels. The performance of the method with respect to other validation techniques has been checked further by testing different topographic maps of the same size.

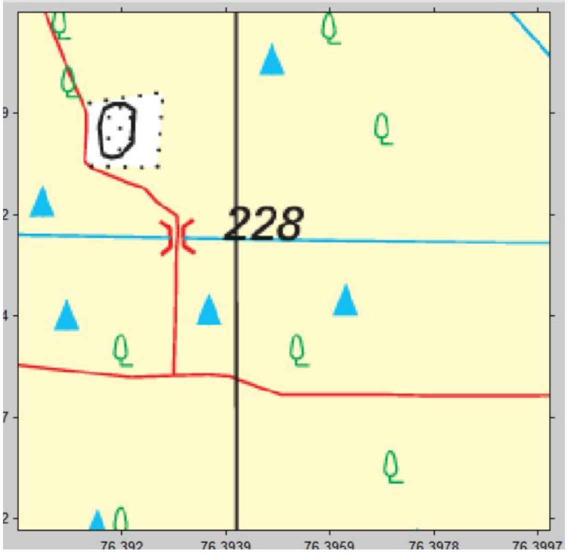


*Figure 6.16(a). OSM 53C7- Sample 4*

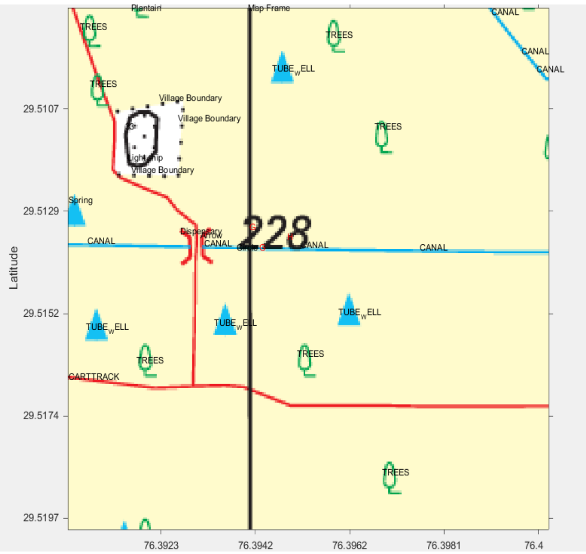


*Figure 6.16(b) ITMUS Interpretation of sample in Figure 6.16 (a)*

*Figure 6.16(c) Intersected/Partial green vegetation extracted by ITMUS from sample in Figure 6.16 (a)*

*Figure 6.16(d) Extraction of text by ITMUS from sample in Figure 6.16 (a)*

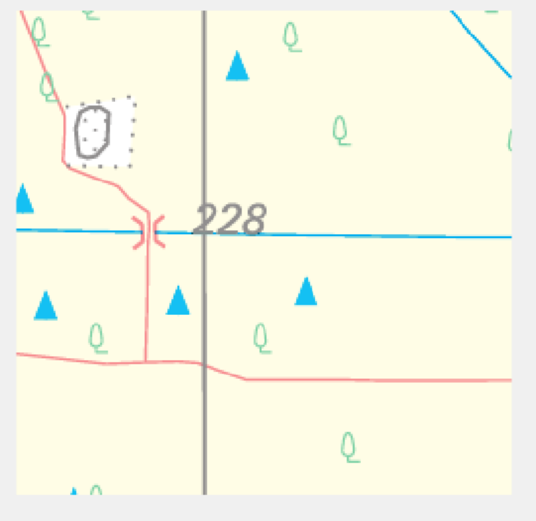


*Figure 6.16(e) Extraction of Hydrological objects by ITMUS from sample in Figure 6.16 (a)*

*Figure 6.16(f) Extraction of road objects by ITMUS from sample in Figure 6.16 (a)*

*Table 6.8 Recognition rate for symbols in Indian topographic map*

| Sr.No. | Symbols | 5-fold cross validation | | | | | Overall Recognition |
|---|---|---|---|---|---|---|---|
| | | **Fold-1** | **Fold-2** | **Fold-3** | **Fold-4** | **Fold-5** | |
| **1** | **Hut** | 100.00 | 100.00 | 100.00 | 92.67 | 96.00 | 97.73 |
| **2** | **Tree** | 100.00 | 92.89 | 96.03 | 100.00 | 100.00 | 97.78 |
| **3** | **Grass** | 90.83 | 92.90 | 89.00 | 91.45 | 91.58 | 91.15 |
| **4** | **Antiquities** | 92.56 | 100.00 | 100.00 | 93.01 | 92.85 | 95.68 |
| **5** | **Metalled Road others** | 100 | 92.90 | 92.89 | 96.03 | 92.30 | 94.35 |
| **6** | **Dry Stream** | 90.76 | 90.70 | 89.87 | 91.98 | 87.99 | 90.26 |
| **7** | **Cart-Track** | 89.87 | 90.77 | 91.45 | 92.78 | 89.02 | 90.77 |
| **8** | **River** | 90.67 | 88.43 | 91.32 | 90.70 | 87.90 | 89.80 |
| **9** | **Broken Land** | 86.90 | 90.54 | 90.54 | 82.00 | 91.78 | 88.82 |
| **10** | **Well** | 89.02 | 82.67 | 89.00 | 86.90 | 89.87 | 87.49 |
| **11** | **Tahsil Boundary** | 82.66 | 78.90 | 81.78 | 91.78 | 89.00 | 84.82 |
| **12** | **Canal** | 91.45 | 89.00 | 89.17 | 85.90 | 87.99 | 84.82 |
| **13** | **Dams** | 87.90 | 86.34 | 92.90 | 90.54 | 88.00 | 89.13 |
| **14** | **Tube well** | 86.90 | 89.97 | 89.00 | 82.30 | 86.15 | 86.86 |
| **15** | **Temple** | 91.90 | 92.89 | 92.89 | 90.67 | 91.00 | 91.86 |
| **16** | **Fort** | 92.60 | 88.43 | 89.87 | 93.02 | 91.45 | 91.07 |
| **17** | **Church** | 88.90 | 87.00 | 92.30 | 91.11 | 88.92 | 89.64 |
| **18** | **Power line unsurveyed** | 72.67 | 80.05 | 78.45 | 75.00 | 76.01 | 76.43 |
| **19** | **Tanks** | 86.90 | 83.67 | 81.78 | 86.90 | 82.30 | 84.31 |
| **20** | **Tower** | 88.78 | 87.05 | 86.90 | 85.56 | 86.90 | 87.03 |
| | **Overall Recognition Rate** | 94.07 | 91.90 | 90.37 | 89.02 | 89.23 | 90.91 |

The developed system has robust enough to understand symbols from all topographic maps developed from Survey of India. The system has been successfully developed on five different topographic maps. USGC and other cartographic map databases are used by few researchers [120, 124, 134, 276] for checking the performance of the map interpretation system, which is not available to others. Many of the research work describing map interpretation systems have not published the recognition result or accuracy. Also, some system performance has been evaluated for different intermediates like template extraction. In some system entropy threshold determines overall recognition rate. As dataset has been different, complexity and noise levels have also been different in the topographic map as compared to any other documents. Hence comparative performance has not been possible. However, self-assessment has been performed. Also, the recognition metric and retrieval metric has been calculated to validate the system.

### 6.5.1 System Validation

As discussed earlier, USGC data and other cartographic map databases which are not easy to obtain, have been used by few researchers [124, 134, 276] to check the performance of the map interpretation system. Hence, cross-validation is used for performance check and also the effectiveness has been tested for National topographic database developed by the Survey of India in different case studies. The samples 4443 training map object data samples and 4443 testing map object data samples have been used to validate MUS. While precision and recall metric has been used to check the performance and accuracy of the system in pattern retrieval. It is also used for plotting precision-recall curve and Receiver operating characteristic curve as done in [15]. The system performance has been checked by implementing contingency table or confusion matrix as provided in Table 3.1. The evaluation metrics have been measured based on the result provided in Table 6.9. It summarizes the training and testing result in a contingency table form.

*Evaluation Metrics*

The efficiency of the search and retrieval is effectively tested by including the output of all the similar images [28, 60, 76]. The performance of retrieval is measured based on the evaluation metrics which are discussed in detail in Section 3.5. These metrics have been deduced for to validate ITMUS's performance as follows:

Recall (for training samples, TR) = $\frac{w}{n_1}$ = 0.9727 and

Recall (for testing samples, TS) = $\frac{w}{n_1}$ = 0.9195,

where, $n_1$ is equal to $w + x$.

Here, $x$ is relevant, but not recognized symbols.

Precision (for training samples, TR) = $\frac{w}{n_2}$ = 0.9421 and

Precision (for testing samples, TS) = $\frac{w}{n_2}$ = 0.8585,

where, $n_2$ is equal to $w + y$.

Here, $y$ is recognized, but not relevant symbols.

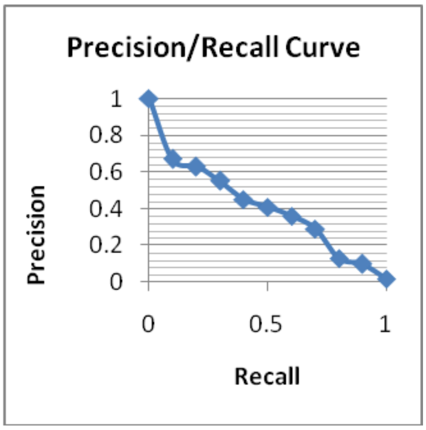
Evaluation metrics of the ITMUS are reported in Table 6.9.

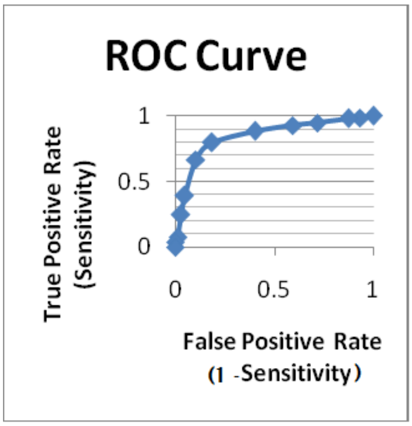
Overall percentage accuracy (i.e. For both training and testing samples) has been calculated using

$$\frac{w}{N} = (4114/4443) * 100$$

$$= 92.77\%.$$

Precision-Recall curve and Receiver Operating Characteristic curve have been shown in Figure 6.17 (a) and Figure 6.17 (b) respectively, for evaluating the average performance of MUS system. In ROC plot, the False Positive Rate (FPR) and True Positive Rate (TPR) have been shown on x- and y-axis respectively.




**(a)** **(b)**

***Figure 6.17 (a) Precision/Recall Curve, and (b) Receiver Operating Characteristic (ROC) Curve***

The fraction of negative objects that are misclassified as positive have been measured by FPR while TPR measures the fraction of positive objects that are correctly labeled. The TPR and FPR are calculated using Eq. 6.1 and Eq. 6.2 respectively.

$$True\ Positive\ Rate\,(TRP) = \sum True\ Positive \Big/ \sum Relevant \qquad \text{Eq. (6.1)}$$

***Table 6.9 Contingency table for accuracy assessment***

| | **Relevant / Correct** | **Not Relevant / Not Correct** |
|---|---|---|
| **Recognized** | $w$: TR* (3678); TS** (3156) {TP-Hit} | y : TR (226); TS (520) {FP} Type-I Error |
| **Not Recognized** | x: TR (103); TS (267) {FN- Miss} Type-II Error | z: TR (436); TS (500) {TN-Correct Rejection} |

*TR: for training samples, **TS: for testing samples

$$False\ Positive\ Rate\,(FRP) = \sum False\ Positive \Big/ \sum Non\ relevant \qquad \text{Eq. (6.2)}$$

False Positive Rate, True Positive Rate, and Area under Curve (AUC) are reported in Table 6.10. In Precision/Recall space, recall and precision have been plotted (Figure 6.17) on x- and y-axis respectively. The recall is equivalent to TPR, whereas Precision measures that number of symbols interpreted as positive that are truly positive. In other words, precision measures the positive recognition of a number of objects that are truly relevant to the actual. The AUC of the Precision/Recall curve is calculated by a stepwise integration of the recall values. The Mean Average Precision (MAP), and AUC of ROC and AUC of Precision/Recall curve has been given in Table 6.11. ITMUS exhibits AUC for precision/recall curve and for ROC curve as 62.35% and 92.78% respectively. The higher AUC denotes that system performs well. It has been reported in Table 6.11.

***Table 6.10 False Positive Rate, True Positive Rate and Area Under Curve (AUC)***

| **FPR** | **TPR** | **AUC** |
|---|---|---|
| 1 | 1 | 0.065089 |
| 0.956722 | 0.98821 | 0.081729 |
| 0.893451 | 0.983467 | 0.133227 |
| 0.734510 | 0.95986 | 0.114795 |
| 0.616734 | 0.939823 | 0.17794 |
| 0.412954 | 0.874567 | 0.175429 |
| 0.195489 | 0.812398 | 0.043205 |
| 0.128730 | 0.678934 | 0.038456 |
| 0.048921 | 0.360565 | 0.010406 |
| 0.028342 | 0.347126 | 0.004387 |
| 0.001921 | 0.054714 | 0.000884 |
| 0 | 0.00323 | 0 |
| 0 | 0 | 0 |
| | | 0.92779 |

***Table 6.11 Mean Average Precision (MAP), and AUC of ROC and Precision/Recall curve***

| | **MAP (%)** | **AUC** |
|---|---|---|
| **MUS System** | 8.02 | 0.9278 (ROC)<br>0.6235(p/r) |

## 6.6 CASE STUDY III

It would be useful if one is able to identify the specific map symbol class, which has been confused with another class during the testing. The confusion matrix is used to overcome the same, which differentiate between the classes classified properly or almost properly and which have confused with another class [168, 190]. As discussed in Section 3.6, to use confusion matrix it is required to have a reference standard to compare with this technique. Human observation or metadata done by Survey of India is used as reference standard. An experimental study has been carried out for the Indian Topographic Map. Encouraging results were obtained by using MUS. The major advantages include identification of the type of land covers, identification of map entities by their abstract level as well as middle-level description, e.g. temple has been understood by MUS as a religious building, also it has been annotated as a temple. The MUS has large scope for further training and will have scope in the improvement in overall classification accuracy. The initial shape feature dataset has been obtained from Legend set interpretation. Then, it has been enhanced with a random selection of a region of interest. In case study III, The 25 sample map regions have been used for training from the OSM topographic map, namely 53C7 (figure 6.18 a.), and 5 different sample regions have been selected from the same topographic map (figure 6.18 b and figure 6.18 c.). To check accuracy and generalization capability of ITMUS, these 5 random regions have been provided as an input for MUS.


***Figure 6.18 a. OSM 53C7 region, (Training image-TR1)***


*Figure 6.18 b. OSM 53C7 region, (Testing image-TS1)*


*Figure 6.18 c. ITMUS interpretation of region in Figure 6.18 b.*

The classification details have been summarized in the confusion matrix as given in Table 6.12. These 5 testing regions contain total 272 map objects. MUS recognize all 272 map objects from testing images. Their true and false recognition results have been considered in terms of feature or object-based classification only. For understanding results and recognized map objects a summary have been given in the confusion matrices (built from the training data set which is named as TD1.. TD9) obtained by comparing the reference data with the interpreted map objects using ANFIS as classifiers as shown in Table 6.12. The confusion matrix table has been utilized to derive the accuracy indices like overall classification accuracy, reference (user) accuracies for the TD1-TD9. The confusion matrices have been derived from the understanding results using Gaussian, and generalized bell functions. The quantitative results obtained by multi-model ANFIS, which has been designed using Gaussian and generalized bell function as summarized in article 5.4.6.5. From Table 6.12, it has been evident that the developed system gives better results for Hut (100%), tube well (92.9%), tree (100%) from the topographic map in the presence of occlusion or intersection of objects.

A measure of the overall interpretation accuracy has been derived from the Table 6.12 by counting how many map objects have been understood correctly by comparing with the reference data and dividing this by the total number of map objects present on region selection:

***Table 6.12 Object Based Confusion matrix using a training data set, TD1-TD9***

| | Reference Data | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Symbols** | **Temple** | **Church** | **Chatri** | **Hut_P** | **Dry Stream** | **Powerline_S** | **Powerline_U** | **Tube well** | **Well_L** | **Bridge** | **Arrow** | **Tree** | **No. of Samples recognized by** |
| **Temple** | 9 | 0 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 16 |
| **Church** | 0 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 |
| **Chatri** | 2 | 0 | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6 |
| **Hut_P** | 0 | 0 | 0 | 56 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 56 |
| **Dry Stream** | 0 | 0 | 0 | 0 | 10 | 3 | 2 | 0 | 0 | 0 | 0 | 0 | 15 |
| **Powerline_S** | 0 | 0 | 0 | 0 | 1 | 6 | 2 | 0 | 0 | 0 | 0 | 0 | 9 |
| **Powerline_U** | 0 | 0 | 0 | 0 | 2 | 2 | 13 | 0 | 0 | 0 | 0 | 0 | 17 |
| **Tube Well** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 3 | 0 | 0 | 0 | 35 |
| **Well_L** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 10 | 0 | 0 | 0 | 14 |
| **Bridge** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 4 | 0 | 22 |
| **Arrow** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 |
| **Tree** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 78 | 78 |
| | 11 | 3 | 11 | 56 | 13 | 11 | 17 | 36 | 13 | 18 | 5 | 78 | 272 |

A measure of the overall interpretation accuracy has been derived from the Table 6.12 by counting how many map objects have been understood correctly by comparing with the reference data and dividing this by the total number of map objects present on region selection:

$$overall\ interpretation\ accuracy = \frac{No.of\ correctly\ recognized\ map\ objects}{No.of\ Map\ Objects\ in\ actual\ map\ region}$$

$$= \frac{9+3+4+56+10+6+13+32+10+18+1+8}{272} = 0.88235$$

The percentage of overall interpretation accuracy has been calculated as

$$= 0.88235 \times 100 = 88.235\%$$

It has been evident that the proposed method gives better results compared to the partial results achieved with ANN [219]. Thus the combination of feature extraction using shape feature-based description and ANFIS based classification will be a better option for topographic map understanding. This work explores a new approach for human based map interpretation. The combination of ANFIS has been tested and evaluated for legend understanding/map understanding system. Optimal feature subset selection and understanding using MUS highly enhances the performance of understanding. However, confusion matrix has been inadequate to define a object-based classification because this measure does not tell anything about how well individual classes were understood.

**6.7 CASE STUDY IV**

In this case study, OSM Geotiff image of 53C7 showing parts of Jind, Haryana prepared by the Survey of India is used to capture 10 training images of size 256×256 pixels. From the training images (Figure 6.19 a), 250 data samples have been acquired by MUS. For evaluating the performance of the trained system at each step of training, five test regions of size 256 by 256 pixels from the OSM topographic map namely 53F7 and 53K1 have been selected. The ITMUS has been trained using training samples selected randomly from the OSM topographic map, 53C7. The five test regions, three from OSM 53F7, and two from 53K1 topographic maps have been selected to test the performance of the system on unseen map images.

Three testing images have been taken from the Indian Topographic Map, 53F7 which shows the parts of Yamunanagar, Haryana prepared by the Survey of India, Dehradun. From the map, three testing image of size 256×256 pixels has been chosen. After combining the outputs of the different layers, the final annotated map for the images has been obtained. The interpretation result of the two testing samples have been shown in Figure 6.19 b and Figure 6.19 c. The testing map is manually ground-truthed, for evaluating the performance of the developed system. The same procedure is followed to rest of the test map regions from 53F7 and 53K1. A comparison of the number of objects in the actual map and those got interpreted by ITMUS have been summarized in Table 6.13. The result shows a recognition rate of 93%. Most of the failures have been resulted specifying that MUS learning model for corresponding map symbols requires further training. The map recognition procedure has been repeated for many other test images, drawn from different maps. The count of errors for these test images as a function of the number of training samples has been provided in Table 6.14a and Table 6.14b. The effectiveness of the system can be seen from the low count of errors and the robustness to noise. From Table 6.13, it can be seen that the results of layer processing have been sufficiently accurate for a map involving ‘compact’ objects such as trees and tanks, and mixed for objects such as rivers, roads, and cart tracks. It has been due to the fact that centroid of these objects often does not make a true representation of the location of the object. For the evaluation of the adopted methodology, three types of errors have been used as an objective measure. These three kinds of errors which have been common in pattern recognition and document image analysis and reported in [83, 97, 122, 190, 272] are given as follows:

(i) Substitution errors—a valid label has been assigned incorrectly to a valid input symbol.

(ii) Deletion errors—a valid symbol has been classified as unknown or undefined.

(iii) Insertion errors—an invalid symbol has been classified as one of the valid symbols.

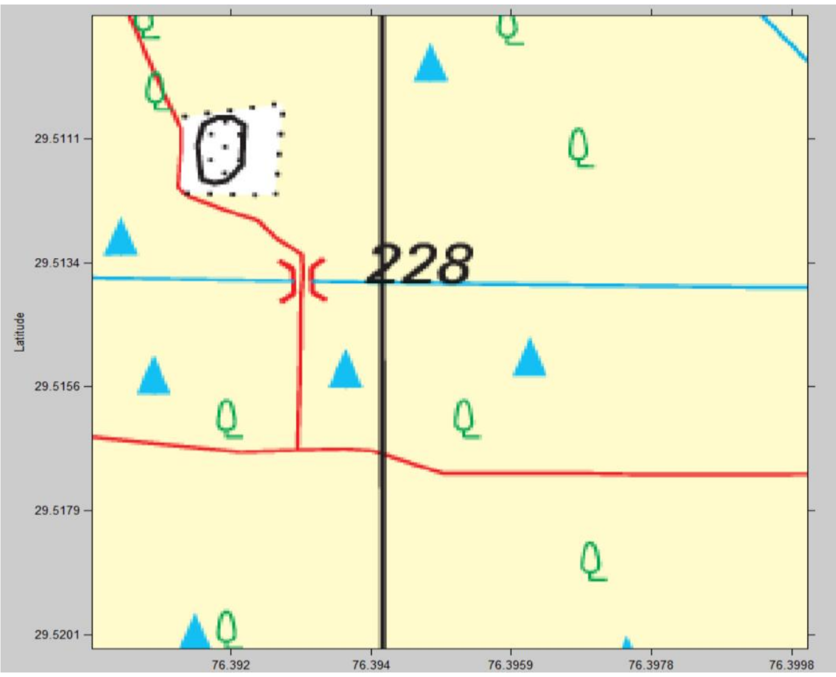



***Figure 6.19 a. OSM 53C7 region, (Training image-TR1)***

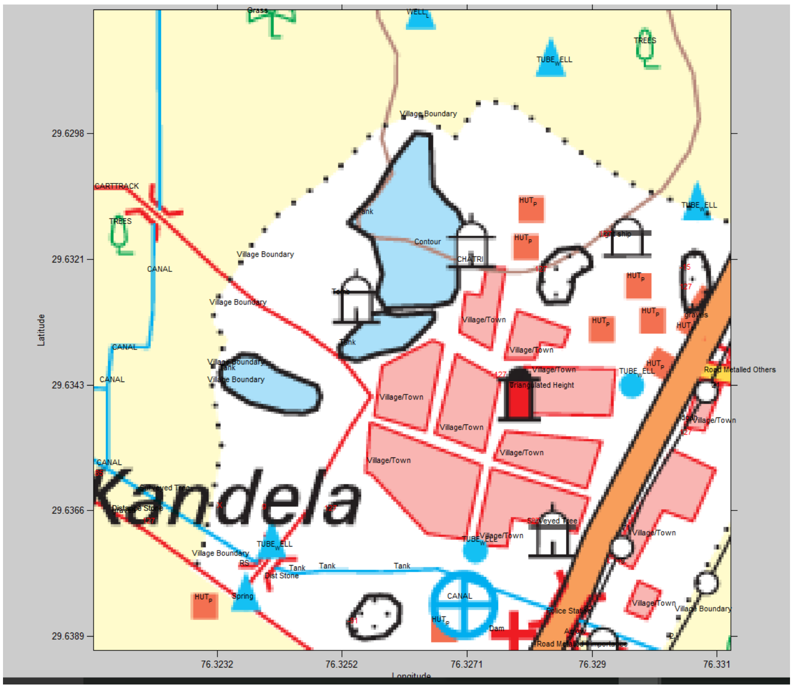


***Figure 6.19 b. Interpretation of OSM 53F7, (Testing image- TS1)***

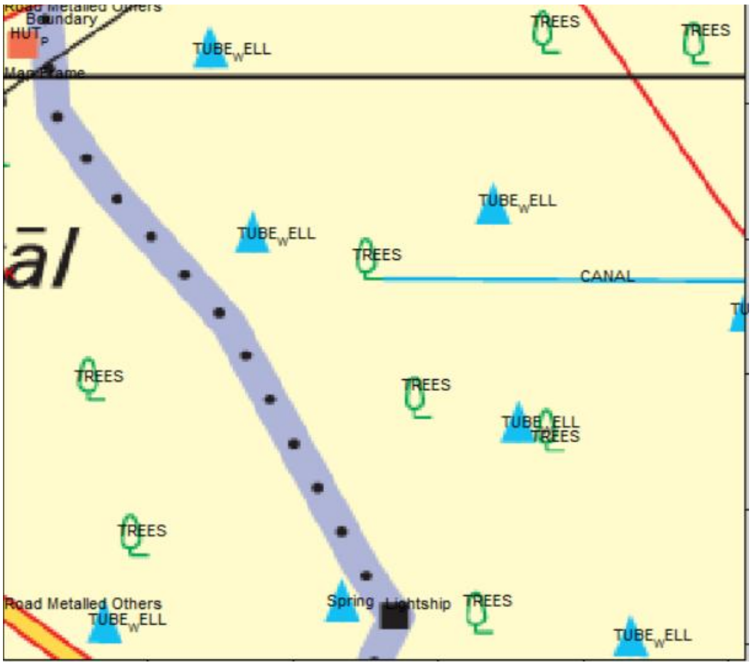


***Figure 6.19 c. Interpretation of OSM 53K1, (Testing image- TS2)***

The interpretation result for the testing regions, TS1 and TS2 have been shown in Figure 6.18. Based on the evaluation criteria, the following results have been obtained: 3 substitution errors (one tree was wrongly identified as grass), 0 deletion errors (one tree could not be recognized) and 2 insertion errors (two components which have actually been part of a dam were recognized as huts). This count will not include the errors of counting four trees and three kinds of grass for components that are actually part of the green field but recognized separately because it remained as separate components in the image. Figure 6.19 enable to analyze the cause of the erroneous valid map object understanding. It shows that the rate of the error types as a function of the number of training samples when considering with minimal mean root square error. Here, it can be observed that the substitution error rate (Figure 6.20) while deletion error rate has been highly affected by the number of training samples. From this observation, it has been clear that the increase in the training samples mainly results in a quick reduction in the number of deletion errors.

***Table 6.13 Comparison of all the objects in 5 testing images and MUS interpreted images***

| Object | Number present in actual test maps | Number present in interpreted test maps |
|---|---|---|
| 1. Tree | **22** | **18** |
| 2. Grass | **8** | **11** |
| 3. Conifer | **4** | **1** |
| 4. River | **1** | **1** |
| 5. Tank | **3** | **1** |
| 6. Hut | **34** | **36** |
| 7. Metalled road others | **1** | **1** |
| 8. Unmetalled road | **1** | **1** |
| 9. Cart track | **1** | **1** |
| 10. Village/town | **3** | **3** |
| 11. Well/tubewell | **3** | **3** |


***Figure 6.20 Error rates when considering map object understanding for 5 test images for various training samples***

***Table 6.14 (a) Count of errors for test maps 53F/7TR1-TR3 and 53K/1TS4-53K/1TS5 as a function of number of training samples (five test map samples)***

| **Error Type** | **53F/7-TS1 (Training samples 50)** | **53F/7-TS2 (Training samples 100)** | **53F/7-TS3 (Training samples 150)** | **53K/1-TS4 (Training samples 200)** | **53K/1-TS5 (Training samples 250)** |
|---|---|---|---|---|---|
| Substitution Errors | **1** | **1** | **1** | **1** | **1** |
| Deletion Errors | **3** | **3** | **2** | **2** | **2** |
| Insertion Errors | **0** | **0** | **1** | **2** | **2** |

***Table 6.14 (b) Error rate as a function of number of training samples gives substitution error, deletion error, insertion error for test maps 53c/7TR1~TR5 (five test map samples)***

| Error rate | Training samples | Substitution Error | Deletion Error | Insertion Error |
|---|---|---|---|---|
| 0.2 | 50 | 1 | 0.2 | 0.05 |
| 0.4 | 100 | 0.3 | 0.25 | 0.18 |
| 0.6 | 150 | 0.2 | 0.32 | 0.2 |
| 0.8 | 200 | 0.16 | 0.35 | 0.35 |
| 1 | 250 | 0.1 | 0.38 | 0.4 |

**The comprehensive intermediate steps result analysis**

The processing and performance of ITMUS has been relied on many components of the system such as pre-processing steps to do layer segmentation, reconstruction etc. Each processing step may account of specific errors. These types of errors are caused due to the conditions in which parameter selection has been made for sub-processes of ITMUS. Due to such errors, the intermediate result of subprocesses gets affected. For example, the segmentation of map image may get over or under segmented due to the values selected for pixel or gray index in pixel/histogram thresholding. The result is that the overlapping or intersection of map objects having the same color could not be resolved. Hence, optimal parameter identification is needed. The reconstruction process is controlled by the variables which are used in the gap filling algorithm. The main problem with this process is the over recovery of the map object. The two independent symbols which are closely spaced and depicted in the same color are also getting connected due to the value of interpixel distance parameter. The value of this parameter is not appropriate in all the cases. Hence, gap filling algorithm may be improved. Further, the structural and statistical features have been extracted and measured. Shape feature descriptor has been created for each segmented map entity. The feature descriptor of such map symbols is treated as representative features in training. The segmented object which is not correctly reconstructed are still measured and it's descriptors acts as a representative description of that object. The text recognition performance is not uniform and ITMUS acts differently throughout the map. It is due to highly varying in style, and orientation of text and linear objects. These are the map objects which are intersected by other map objects. The intermediate steps result analysis has been summarized in Table 6.15.

The processing steps, error types, causes and difficulty in processing have been identified. Based on this, a comprehensive result analysis has been done. For comparative result analysis, system has been categorized into 4 parts. Each part which is susceptible to some kind of errors, causes of their occurrences and effect on intermediate results have been listed in Table 6.15. Also possible solution has been identified for each error type. The intermediate steps result analysis has been done. The result analysis has been done for OSM 53C7 sample-5 which consists of total 13 blue object instances as shown in Figure 6.21 a. Segmentation has been carried out to separate blue map objects. In segmented blue layer, 15 blue object instances has been appeared due to the gap or hole created in layer extraction as in Figure 6.21 c.. In figure 6.21 d, reconstruction has been performed and obtained image shows 13 blue instances. Features of these objects have been measured to form feature descriptor. The previously trained ITMUS has been tested/evaluated on image given in Figure 6.21 a. The interpretation result has been obtained which is shown in Figure 6.21 b. It has been observed that out of 13 blue object instances, 9 instances has been interpreted correctly. 1 remains uninterpreted; 3 misinterpretation has been occurred. Thus, feature measurement and training has scope to investigate further.


*Figure 6.21(a). OSM 53C7- Sample 5*


*Figure 6.21(b) ITMUS Interpretation of sample in Figure 6.20 (a)*

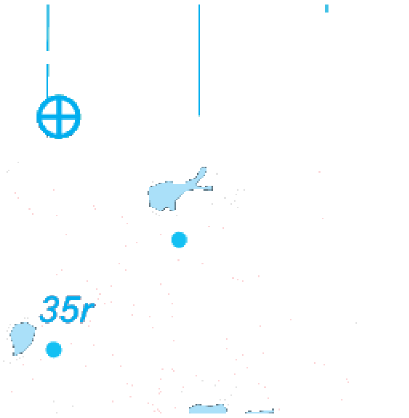



*Figure 6.21(c) Segmentation of blue objects by ITMUS from sample in Figure 6.20 (a)*

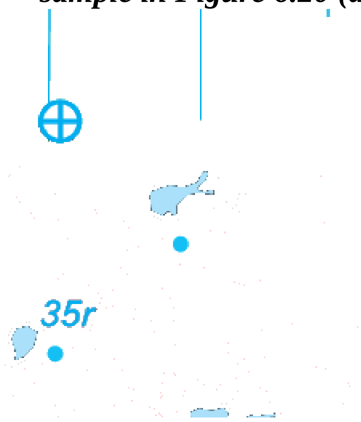



*Figure 6.21(d) Reconstruction by ITMUS from sample in Figure 6.16 (c)*

*Table 6.15 Intermediate steps in Result Analysis*

| Processing Step | Error Type | Condition | Effect | Possible solution | Layer Analysis |
|---|---|---|---|---|---|
| Segmentation | Over segmentation/under segmentation | Due to parameter selection in pixel/histogram thresholding | Overlapping or intersection of map objects which are having same color could not be resolved. | The optimal segmentation method has to be investigated. | Blue object: Actual: 13 Segmented:15 |
| Reconstruction | Over recovery (joining of | Parameter selection is | The two symbols | Reconstruction algorithm | No. of instances 13 |

| | | | | | |
|---|---|---|---|---|---|
| | isolated symbols) | done randomly. | which are same in color, but isolated are also getting connected due to the value of interpixel distance parameter. It is not always appropriate. | can be improved. | |
| Feature extraction and measurements | Structural and statistical features have been extracted and measured. Shape feature descriptor has been created for each segmented map symbol. | Its performance depends upon the previous segmentation and reconstruction process. | The segmented objects which are not correctly reconstructed are measured. The feature descriptor of such map symbols is treated as representative features. | However, ANFIS has been trained using all features set which represents the varying objects of the same kind. Iterative training has been required. | 13 Feature vector containing description |
| Recognition | The recognition rate of text and linear objects is | It is due to highly varying in | The orientation has been | Text has been further oriented to | 9 blue instances are interpreted.T |

| | | | | | |
|---|---|---|---|---|---|
| | less as compared to other objects. | style, and orientation of text and linear objects. These are the objects which are intersected by most of the times. | measured in shape descriptor, but still ITMUS could not measure as well as representin g it effectively | get it interpreted correctly by ITMUS. However, there is a need to investigate the recognition of only linear objects. | ext wrongly interpreted. |

## 6.8 DISCUSSION

The development of the Indian topographic map understanding system uses an integration of technologies such as image processing, pattern recognition, and adaptive Neuro-fuzzy inference system. The design process of the ANFIS models has been accomplished with the proper number of initial membership functions and has employed the learning process to generate a set of fuzzy if-then rules to approximate the desired output. The developed system performs operations like a human map reader. This concept facilitates many operations like legends shape and pattern recognition, initial knowledge creation without a human expert, map segmentation, use and evaluate existing knowledge and adapt it recursively like a human brain. The legend symbols line, dot or structure matches with static rules to derive the semantic meaning of legends. Initial rules have extracted based on legend structure knowledge, which has been further tuned by ANFIS. Also, designed multi-model ANFIS has the capacity to learn more data and generalize well on the unseen region from the topographic map. The main motivation behind using feature based adaptive Neuro-fuzzy has been its resemblance with human visual map understanding where the map object has been specified as a feature vector presented. As understanding has been based on structural features and incomplete or vague feature set that has been handled by FIS. The symbols touching with other symbols or letters and numbers have been interpreted with good accuracy. The topographic map symbol database has been generated which includes local coordinates, geo-location, structure and shape feature. Also, geospatial map layers have been stored in image form, i.e. .tiff file, as well as layer-wise database, have been stored in an excel spreadsheet file.

The developed ITMUS have employed image processing and artificial intelligence technology. The developed system identifies conceptualization present in map objects and implements multi-model based intelligent information understanding approach for Indian Topographic maps. Indian Topographic map understanding system (ITMUS) has been developed which initially understands legends and have acquired structural knowledge and semantic description of legends. The static rule based hierarchical matching has been applied during legend recognition. Thus ITMUS creates legend structure description data set and treats it as the training set. The ITMUS has been trained on this data and tested on various regions on a topographic map. It has been proven that the system has the ability to generate a priori knowledge as well as perform on it and system performance has been enhanced based on the learning ability. The system's working and performance have been tested and validated using quality measures. The system yields very good understanding about map symbols not only in semantic meaning, but also in geospatial context also.

The ITMUS for automatic extraction of information from Indian topographic maps has been developed and tested making use of images from five OSM topographic maps spread over different regions in India. The system has been designed using two GeoTiff Indian topographic maps and legends set present in each map which consists of 117 legend images and tested with five GeoTiff Indian topographic maps. Working of ITMUS comprises of many operations like legend's understanding (based on shape and pattern primitives), automated training data generation, map segmentation, use and evaluation of existing knowledge and adaptation to it recursively. ITMUS provides interpreted topographic map which may be used for automatic map understanding. Output also contain layers of thematic information in geo-located images stored in the .tiff file as well as in table forms containing local coordinates, geo-location, the structural features etc. To evaluate and validate system with respective to a different output, different case studies have been done in response to different parameters. The output of the system has been evaluated for random selection of a region of interest from 5 GeoTiff topographic maps. MUS have been trained for various sample regions selected from 53C7 and 53K1 OSM topographic map. To carry out a different case study, map regions have been selected from 53C7, 53F6, 53F7, 53F11 and 53K1. The testing regions selected from 53C7 and 53K1 have been sufficiently different from training regions. 53F6, 53F7, 53F11 are the OSM topographic map data which have been used as a testing and checking data to check the generalization capability of MUS as regions selected from those maps are completely unseen to MUS. The evaluation operations have been carried out empirically using many experimental studies on test images. It has been found that the overall recognition rate of the system is 90.91%. Further, the system has been assessed on three other different criteria, i.e., its overall completeness, correctness, and rate of correct recognition. The criteria have been found to be 0.93, 099 and 93.79% respectively. The ITMUS have been evaluated on a database of 4443 (Total 9 datasets of the topographic map, namely, TD1 to TD9) map symbols as described in case study II. The results showed that the developed method has an overall percentage accuracy of 92.77%. From case study III, the confusion matrices have been obtained from the classification results and its quantitative results reported. It has been clear that the developed system gives better results for hut samples (100%), tube well samples (92.9%), tree samples (100%) from the topographic map in the presence of occlusion or intersection of objects. A measure of the overall classification accuracy derived is 88.235%. The Geological Survey has set criteria for the successful interpretation system. According to Anderson [19], the accuracy of interpretation of the generalized levels is satisfactory when the interpreter makes the correct interpretation 85 to 90 percent of the time. Here, greater interpretation accuracy has been attained by ITMUS for Indian topographic map. Case study IV provides a rate of the substitution, deletion and insertion error types as a function of the number of training samples have been considered with minimal mean root square error. It has observed that the increase in the training samples will reduce the number of deletion errors.

Thus, the development of ITMUS has provided a more general, robust, and reliable solution in the framework of the geospatial map understanding/interpretation system. The technique that has been developed has shown the very encouraging level of performance for the problem of topographic map understanding. Thus, the working and validation system shows that the feature based shape description and soft computation based understanding approach have become a reality to understand the Indian topographic map automatically.

# CHAPTER 7
# CONCLUSIONS

## 7.1 INTRODUCTION

The topographic map is characterized by the use of the potential of a geographical and geospatial data to provide large scale details and geospatial information in layers. However, automated extraction of information from the topographic map is very difficult due to the interconnectedness and wide variety of objects in a map [144, 211]. The fully automatic and generalized solution does not exist so far in the literature. So, there is a great need of a system which is capable of extracting data or information from a Topographic map and provide an output which is useful for the development of automated Geo-based information system.

In this study, ITMUS, a system capable of extracting geospatial information from topographic map has been developed. The development of LUS module is a prerequisite. As Indian topographic map understanding is comprising of two major subsystems, two main outputs have been obtained in two subsystems. The legend understanding subsystem has been provided with legend set from Indian topographic map and obtained interpreted form . The map understanding subsystem is provided with a region of interest from the topographic map as an input and produces interpreted region, thematic map layers, and geolocation based data set as major outcomes.

The research has been motivated by the growing demand for advanced information extraction and map analysis techniques in geoinformation science. The research has been influenced by the need to devise a generalized method for information extraction in an automated fashion to complement manual method such that time invested in the manual extraction of information, which possesses inconsistencies and bias can be reduced to the optimum. Human lacks consistency but supremes in pattern recognition and analysis. Human interprets the highly complex, interconnected or overlapped objects of topographic map quite easily based on learned map legends. In the research work, this analytical model of human map understanding has been emulated using a human mentation and learning process. The integration of humanistic approach and computer/machine methods for automated information extraction and automated understanding of topographic map has been proven effective to the automated map understanding. The first phase in human map understanding process is reading of map legends which use color and geometrical appearance of legend. To emulate this phase, LUS has been devised. A legend has been measured and described using a set of shape and structure parameters, each of which has been used at a different level of matching.

The LUS performs static rule based matching and legend recognition, which is consisting of structure and shape parameters in premise part and semantic description of the legend in consequent part in a hierarchical manner. The LUS has interpreted the legends set and has created legend structure description data set. The legend structure description data set has been partitioned into 9 training set libraries based on map object categories as suggested in Data model for digital cartography which is prepared by the Modern Cartographic Center of Survey of India [215]. The second phase in human map reading is to utilize the legend data for reading and understanding of objects/symbols present on a topographic map. This phase has been emulated by MUS which uses legend structure data to acquire knowledge about the legend. However, understanding of topographic map by the computer system is not easy due to high density and overlapping of map objects. To overcome the problem of complexity, a “peeling onion strategy” has been adopted, where the continuous subtraction of the already recognized map layers has been carried out to simplify the processing of the rest of the complex layers. For map object interpretation, "correlation theory of brain" has been employed. It has been done by designing FIS to infer rules from initial training set libraries. In MUS, the genfis commands have been used to create membership functions to configure multiple ANFIS. Once the initial membership functions have been created, the training of system has been carried out by providing legend structure data and membership function created by FIS.

After the training of system has been finished, the final membership functions and training error have been produced. The checking data have been used along with training data to increase possibilities to make a system understand map objects. Also, the system performance has been evaluated by providing input data set into the fuzzy system through the selection of a region of interest from topographic map. These data structure consists of a shape feature description of map objects present in that region but semantic meaning have not been presented in that data. The output of ITMUS represents the semantic description code and provides a resultant understanding about the map object. The semantic code has been measured on the basis of correlations between the desired context and learning content. The trained system has been evaluated on several regions on a topographic map. The training set has been increased incrementally and training has been performed again once scarce of topographic map data became available. The training has been performed iteratively till system learns various feature vectors and varying patterns of the same object and generalizes well on unseen topographic map data set. The whole system has been tested for variation of system output in terms of the number of performance measures. Also, effectiveness and robustness of ITMUS have been checked on training as well as on testing images of topographic maps. The performance of the system shows promising results, which have been presented through four independent case studies. The objective of the study to develop a system which is capable of understanding Indian Topographic map automatically has been met through the development of ITMUS.

## 7.2 OVERALL CONCLUSION

The major outcome of the research work is the development of automated Indian topographic map understanding system (ITMUS). Also, the development of the LUS has been accomplished to support the legend knowledge acquisition process. This research work has identified a suitable theoretic concept and most generalized methodological framework for extracting geolocation based information from the Indian topographic map. The result of the research has added a significant knowledge to geoinformation science.

The capabilities of ITMUS have been determined based on the output products which effectively conveys the interpreted information to end user. Using ITMUS, Indian topographic map has been viewed in terms of a hierarchical arrangement of higher levels of abstraction and its understanding. A resultant response which has been derived from MUS represented in the form of an interpreted map (i-map). The i-map representation deals with presenting the annotated/labeled topographic map objects inside the ROI which has been selected by the end user. ITMUS provides the intermediate description of map objects. ITMUS also provides insight to the user to extract the color based and feature based layers along with geolocation information. The ITMUS generates thematic map information in .tiff and in .tab form. The thematic map layer contains geometrical and geospatial information which has also been stored in matrix form, excel spreadsheet form as well as text files. All the output files are in geographical system supported format. The map analysis report includes the semantic meaning of the interpreting object, it's geometrical feature values, pixel location, and corresponding Geo-coordinates. The ITMUS has incorporated with inbuilt accuracy assessment, a utility for both symbol and layer extraction assessments. Thus, the ITMUS provides the end products, which may be used in several geospatial activities. The system’s capability and applicability have been checked by end product's usefulness. ITMUS also stores boundary pixels of objects in each layer which may be used to produce vector data and may be used further in Geospatial activities. The ITMUS stores interpretation results of legends set in excel worksheet and in .pdf file format. Thus, the developed system provides an alternative to manual map understanding by contributing automated geolocation based information extraction and retrospective map analysis report for computer-based information processing.

The topographic map understanding system presented in the research work have been characterized by (a) development of an approach to recognize representative structure and shape of a map objects (such as endpoints, branches, area, solidity, etc) [269]; (b) design of a fuzzy inference system to generate rules base from legends description data set; (c) design of multi-model ANFIS to learn feature descriptions and make the system to understand the map symbols; (d) humanistic approach which is based on learning capability and mentation process which effectively handles uncertainty have been devised for map object understanding using integration of ANN and FS; (e) recognition of toponym layer using ANFIS model which has been incorporated in MUS kernel.

For the development of ITMUS, image processing routines, and soft computation based technique have been integrated. The intersection and overlapping conditions in topographic maps have been handled adequately by performing color-based segmentation and gap filling algorithm prior to the recognition and interpretation. The developed ITMUS have used multiple ANFIS models to reason efficiently various types of map objects which can be distinguished on the basis of color and shape peculiarity at various levels of abstraction. Human tendency to deal with uncertainty has been emulated by the fuzzy inference system. Human reasoning based on learning and experience has been emulated by the adaptive neural network. A human based map understanding system with feature-based and learning based techniques have been incorporated along with legend set prior knowledge acquisition capability. It has been possible because conflicts can be merged without much effort in the human based system. This has been incorporated by feeding the changes back to the previous levels of the system and retraining the conflicting objects. On the actual map, part of an object may not be fully visible because they may be confused with other map objects. Such an object may not be measured or quantified correctly with a representative feature descriptor. However, LUS generates initial legend training set, consisting of a set of features describing legends which are complete in nature. The MUS uses this training set for initial rule generation. The adaptive neuro-fuzzy model which has been designed in MUS anticipates the variability and vagueness of feature descriptors describing partial, confused and variable map objects. Thus, these conditions have been anticipated by soft computation methods instead of using several complex image processing operations.

The ITMUS has been tested and evaluated by considering different parameters. The ITMUS has been trained for various sample regions selected from 53C7 and 53K1 OSM topographic map. The OSM topographic map data, namely 53F6, 53F7, 53F11, have been used as a testing data to check the generalization capability of ITMUS. The overall completeness and the overall correctness of the system are 0.93 and 0.99 respectively. The rate of correct recognition obtained is 93.79%, which is encouraging. The system has been validated using 5 fold cross validation technique which gives 90.91 % overall recognition rate. The Overall percentage accuracy and accuracy as a function of the size of training set have been measured and obtained as 92.77% and 88.235% respectively. The result shows that the robust and reliable topographic map understanding system has been developed. The development of ITMUS exhibits characteristics which have been outlined below:

1. A novel system, ITMUS has been developed for automatic extraction and acquisition of information from the Indian topographic map;
2. The adaptive Neuro-fuzzy system is investigated the first time for map understanding and incorporated successfully.
3. Modularity in subsystem design enables to adapt the system to understand topographic maps of another country also.
4. System scope is not limited by a rigid framework, i.e. the system is capable of including different map object semantic, if found any in the complex territory. It is also possible to interpret map symbols, whose corresponding legend is not defined in legend set but occurred in actual map. Such a situation can be overridden by including such object in a specific topographic category or training library.

## 7.3 SALIENT CONTRIBUTIONS

The overall contributions to the field of map understanding systems development that have come out of this study are discussed below:

1. A most generalized and robust system that can be applied to any document containing signs or graphics.

The generalized approach to human understanding has been emulated. The characteristics of human understanding like uncertainty handling, mentation process to perceive objects or training-learning phenomenon has been devised through soft computation techniques. So any kind of image or graphics which contains signs or symbols can be understood by computer through this approach. The system has been fully automatic and has worked standalone without any human intervention. The system has not relied on any feedback or knowledge about the topographic map from a human. No such topographic map understanding or interpretation system has been found in the literature. Thus, the development of the generalized approach has provided the robust framework for any kind of graphics /symbolic document analysis.

2. An automated system capable of understanding Indian topographic maps automatically.

The combination of statistical pattern recognition with shape features based map object representation and ANFIS technologies on developing an understanding system that has been a novel approach. Also, human based map understanding approach is missing in the literature. The system has scope for training for evaluating it on large series of Topographic map by an increase in the training data set. The developed system's functionality has been validated for interpretation and classification on present data set in hand. The system has met the desired objectives and could be utilized with other forms of geospatial activities. Also, the development of the system provides a general framework in which new map object's semantic may be incorporated as well as any legend driven system can be developed based on the present investigations. ITMUS can be easily adapted to understand other maps or graphics documents.

3.Development of a Neuro-fuzzy approach for symbol pattern understanding.

The system development has been made by integrating image processing techniques for feature extraction with the cognitive capabilities into a Neuro-fuzzy model for enriching it. Neuro-fuzzy technology has not been employed in already existing works in the field of map interpretation or understanding. It is because the initial rule generation is not easy. Also, crude domain knowledge extraction for an initial parameter setting of the Neuro-fuzzy system has not gained attention in research community working on map interpretation. The human way of topographic map understanding and reasoning capabilities about the topographic map object class have not been implemented in any system.

In the developed system, an initial knowledge is gained from legend set understanding through if-then rules which are further learned by the system. It follows an exact way which human always uses to read a map or understand any geographical portray. The developed system is trained prospectively to understand topographic map within multiple views when extracting information concerning the semantic description of topographical map objects explicitly modeled on a map has been made.

4. The indefinite and imprecise topographic map data handling using fuzzy approach.

Integration of pattern recognition and neural fuzzy inference for Indian Topographic Map understanding is done using design and development of low-level image processing as well as high-level computer inference through an automated system. The designed system follows the Sugeno approach for inference mechanism. The FIS system uses AND logical combination of inputs in the rules. The developed system configures ANFIS model with the following properties such as ‘type-Sugeno’, ‘and method-product’, ‘or method probabilistic’, as well as ‘implication method-product’, ‘aggregation method-maximum’, ‘defuzzification method-weight average’.

5. A hierarchical approach to instantiate topographic map into an abstract level of description.

For a better understanding of object instances from their structure to concept or semantics and from simple layer to more complex layers, the hierarchical approach has been used. Feature-based classification is used to retrieve map objects and features of a multi-temporal series of topographic maps. Subsequently, the map objects are compared with their geometric features to detect its semantic meaning in an operational way which is based on the correlation theory of the brain.

ITMUS provides very good interpretation for independent symbols. Howerever, in case of noisy symbols, it sometimes fails to interpret. Thus, ITMUS exhibits weaknesses in identifying partial, intersected or overlapped symbols. Based on testing on noisy map object (Table 6.7), it has been clear that ITMUS interprets 12 out of 16 partial symbols. It interprets 62 intersected map symbols out of 82 intersected map symbols. Out of 29 overlapped map symbols, 24 map symbol are interpreted. Thus, the number of partial, intersected and overlapped map symbols missed by ITMUS are 4, 20, and 5 respectively. Hence, the prospect of further research includes the optimal segmentation algorithm and feature description which may be defined in relation to their neighbouring objects. Another limitation of ITMUS is that it faces difficulty in dealing with the region where text touches the symbol with same color. It may have an effect in the overall recognition of symbols and toponym for location base analysis. But both limitations are constrained by training aspect. Moreover, variations in text properties (e.g., text color, text size, text style etc.) can also occur within maps of the same types or even a single map page as a result of the differences in map complexity, and inconsistencies of graphical quality in the original map. Thus, the ITMUS performs differently in various parts of one map. Understanding such recognition sensitivities to variations in graphical properties can further improve the ability to forecast the potential for automatic text recognition and highlight possible recognition errors automatically.

Most map processing systems cannot process different types of maps automatically, which is, in particular, true for text recognition. This is because maps have a complex layout in which text labels appear in various forms, colors and size categories, which requires manual identification of processing parameters and system training. However, ITMUS show an increasing potential which may be further enhanced to establish text recognition systems that provide reliable solutions across different types of maps, but their accuracy can vary significantly across map types.

Thus, the overall research contribution of the study have been summarized as given below:

1. Development of a human based map understanding approach has been made possible using Neuro-fuzzy method for topographic symbol understanding.

2. Legend-based map understanding that use morphological operators combined with shape descriptors.
3. Shape description vagueness due to map object's pattern variability have been management using fuzzy approach.
4. Development of integral of feature-based approach and learning based approach.
5. Design and development of a low-level vision to high-level vision, computer enabled automated understanding system.
6. Results and output of ITMUS can be taken up to geoinformation system for further analysis and work.

The novel contribution of the research work has been given as:

1. A generalized and robust approach has been devised which can be applied to any kind of graphics or symbol understanding system.
2. Analytical model of Human based map understanding is emulated for the development of topographic map understanding system
3. Multi-model ANFIS is designed as an intelligent module to understand the topographic map.
4. Geo-location based thematic layers and topographic map data are generated

## 7.4 FURTHER RESEARCH SCOPE

The prospect of further research includes the optimal segmentation algorithm and feature description which may be defined in relation to their neighboring objects. Another research outlook is how to deal with the region where text touches the symbol with same color. It may have an effect in the overall recognition of symbols and toponym for location base analysis.

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# APPENDIX- I

# MODULE DETAILS AND PSEUDO CODE OF INDIAN TOPOGRAPHIC MAP UNDERSTANDING SYSTEM (ITMUS)

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## Main Program or Start up module for subsystems

-----------------------------------------------------------------------------------------------------------

The system starts functioning from this module. The start-up module initializes two main submodules one for LUS and another for MUS. These two main submodules define and declare variables and submodules used by them. The schematic diagram of main modules and submodules is given in Figure I.1.

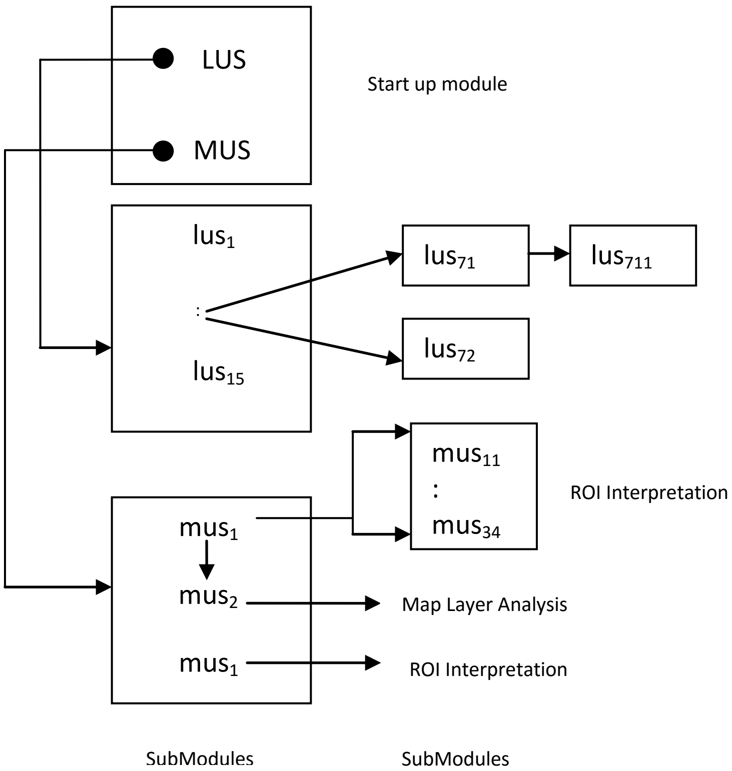


*Figure I.1 Schematic diagram of main modules and submodules*

### Start up module

Start LUS module

Start MUS module

-----------------------------------------------------

**LUS module**

**-----------------------------------------------------**

**%**Prompt user to enter legend set

%

Declare image variable and handle;

Display legend set;

%

%Preprocess the legend set.

%

Define filter variable

Filter legend imahe

Perform RGB to gray conversion

Preserves all intensities below 240.

Clean image

Dilate image

%

%Define bounding box.

%

Define Variable for region properties using bounnding box.

Measure region properties inside the bounding box.

%

%Crop each legend region.

%

while number of objects inside bounding box

go to color code book generation

%

%Color Code book Generation.

%

Perform histogram thresholding to identify gray level values.

Identify cut level in RGB

Pixel and gray index thresholding to suppress other colors and assign 255 to selected range;

Assign code pair values in image variable using

a = Out(i,j,1)/255;

b = Out(i,j,2)/255;

c = Out(i,j,3)/255;

Color_code(i,j) = a*100 + b*10 + c;

%

%Gaps or holes removal

%

Allocate size of object array

return the length of the first 3 dimensions of obj.

Initialize flag varable as zero

Scan each row and each column and read it in another variable

If it does not matches with color code then increment flag

If flag is greater than equal to 7

then store i-1 th value to i th value of color channel

Continue for all rows and all columns

Identify number of element present in

%

%Find and analyze the object in area

%

Define string array variable;

Define and initialze object array;

Assign r, g, b values by calliing variable of object array

```
r = Out(:,:,1);
g = Out(:,:,2);
b = Out(:,:,3);
```

Perform layerwise or color code wise object/legend analysis

for r=0, g=0, b=0

allocate 'black' value to color property of string array variable

%

% Perform shape analysis shape analysis of object found in that layer

%

if ~isempty (element)

return structure of element

Generate convex hull on legend region

Find connected component in hull

Measure structral Properties.

Find a number of branches, end points, extrema, etc.

Static IF-THEN rule based matching

Derive Semantic meaning by evaluating IF-THEN

Write down derived meaning and structural measurement in legend data set.excel file.

Display semantic meaning at each legend present in legend set.

%

%End of LUS

--------------------------------------------------------------------------------

--------------------------------------------------------------------------------

%FIS Design and training of ANFIS

--------------------------------------------------------------------------------

Load input and output data pairs from 9 training set libraries derived from legend set description dataset

Design FIS total nine FIS using genfis1 or genfis2 or genfis3

Given n candidate inputs, a subset of “k” inputs is selected as an input to the ANFIS for training.

Normalized train and test data.

The ANFIS model is constructed.

ANFIS model is trained by training data. Step 5: Evaluation with test data.

Train using hybrid learning algorithm

Evaluate anfis with test data using evalfis.

Repeat training until system generalizes well

%END ANFIS

----------------------------------------------------------------------

MUS module

----------------------------------------------------------------------

%Design GUI

Main Menus

'File'

'View'

'Tools'

Call function *roi_rect*

'Start'

'About'

File Menu

'Open Topographic Map'

Call function *MapGeoConverter*

'Print'

'Quit',

View Menu

'Zoom In',

'Zoom Out',

Tools

'Select Area of Interest'

Call function *roi_understand*

'Assessment/Interpretation',

Call function *Mass*

Start Analysis

'Layer Analysis'

Call function *Amap*

'Toponym Understanding'

Call function *toponym*

'Black','Callback'

'Red','Callback'

'Blue','Callback'

'Brown','Callback'

'Final Understanding','Callback'

'Clear',

'Human Interpretation of Legends'

store gui data

%End Design GUI

%MapGeoconverter

Initialize handle, and image variable;

Create axes graphic object;

Prompt user to load the topographic map.

Load topographic map;

Read map area from whole sheet and strore into variable;

Retrieve corner coordinates from Geotiff topographic map.

Make reference matrix

Create *la* and *lo* variable to assign to latitude and longitude values obtained from reference matrix

Obtain Latitude limit and longitude limit

assign map , filename, reference matrix and pathname to map handle.

Set Latlimit on Y axis

Set Lonlimit on X axis

Bind map handle to gui data.

%End MapGeoconverter

%ROI Understanding

Load GUI data into structure variable.

Initialize variable to get cursor position.

Load selected region into variable.

Convert map cordinate to pixel coordinate

Convert pixel coordinate to latitude longitude coordinates

Calculate reference matrix for region of interest

Call function symb_l

Save gui data.

% End ROI_Understanding

%Map accuracy assessment

Load gui data

Load map region form map array

Call function Color_mx

Separate layers based on color code.

%End Mass

%Map Analysis

Load and initialize variables

Separation of foreground background objects based on pixel thresholding

Separation of Symbol, non-symbol based on weight matrix

Remove already recognized layers and

Reconstrcut layer.

Call function symb_l

%End Map Analysis

%Map object understanding

Initialize variables,

Assign handle to gui data

Find object

Define and apply filter

generate color code

initialize matrices

Divide image into layers rgb based on color code

```
for i = 1 to m
    for j = 1 to n
        c = color code
        if c ~= 0
            Black(i,j,:) = 255;
        endif
        if c <1 | c> 3
            Blue(i,j,:) = 255;
        endif
        if c ~= 4
            Green(i,j,:) = 255;
        endif
         if c ~= 5
            Brown(i,j,:) = 255;
         endif
        if c <6 | c> 10
            Red(i,j,:) = 255;
        endif
        if c ~= 11
            Yellow(i,j,:) = 255;
        endif
        if c < 12
            Backgr(i,j,:) = 255;
        endif
    end for
end for
```

Separate background based on color code

Remove background.

Gap filling and Layer reconstruction

Perform layerwise interpretation of foreground object based on color code.

Initialize variable for map object intermediate descriptors.

Perform Connected component analysis

Load connected pixels into pixel array

Measure properties of connected component.

Determine number of connected components into region.

Sort pixel list.

For 1 to number of connected components

scan pixel list

create minimum bounding parallelogram

calculate minimum and maximum values of bounding parallelogram

based on these values crop object region for further processing

Call function gap_fill_algorithm

Analyze object shape

Call function obj_shape

Initialize string array.

Generate convex hull image from binary image

Find connected elements in binary matrix

Create label matrix from obtained structure

Measure shape properties like euler's number, eccentricity etc.

Initialize input DSN which is string array containing map object's semantic description.

Store empty string for semantic meaning, latitude , logitude, and rest of 8 shape descriptors in excel speadsheet.

Read data from spreadsheet from 4th column i.e. read shape parametrs and their values only into a call.

Convert cell into matrix form.

Provide these shape description as a testing data to trained ANFIS model(output fismat structure)

Evaluate trained ANFIS model with the testing data measured from ROI.

Obtain Measured output.

Convert output value into 8 bit signed integer.

If value is greater than 0 and less than length of Input DSN

then retrieve semantic meaning from input DSN string array from the location which matches with output of ANFIS.

Set semantic string to 1 and convert number to string form to return semantic meaning for object.

Write derived semantics of objects at respective geo location of object.

Write map object details in excel file and text file.

Store result in output variable in string array format.

Append intermediate string array with recgnized and interpreted map object.

bind GUI data.

%End Symb_l

% Accuracy Assessemnt - Compare reference data and interpreted data.

Open Interpreted text file

Read reformatted data from text file into file variable, C{2}

Close file.

Open standard Referenced file.

Read reformatted data from text file into another file variable, C1{2}

Close file.

Append or merge tabe entries

```
C2 = [C{2};C1{2}];
Remove redandant entries and load into separate table, A1
B = {};
for i = 2 to length(table rows)
    num = 0;
    for j = 1 to length (interpreted table entries)
        if strcmp(C{2}(j,1), A1{i})
            increment number of instances
        end
    end
    B = [B; num2str(num)];
end
B1 = {};
for i = 2: length(table rows)
    num = 0;
    for j = 1: length (Referenced table entries)
        if compare first 10 characters of string at C1{2}(j,1) and A1{i}is true i.e. 1 then
            increment number of instances
```

```
        end
    end
    B1 = [B1; num2str(num)];
end
Create 2-D graphic table GUI component
set(t, 'ColumnName', {'Symbol', 'Reference Data', 'Interpreted Data'});
 Display  [A1(2:end)  B1 B]
% end accuracy assessment

% Perform layerwise understanding
Initialize figure handle;
Create axes graphics object
Load GUI data
Display ROI
Create menu for 'Layers'
                                    Land Cover
                                    Forest
                                    Cultivated
                                    River Bed
                                    Vegetation
                                    Urban Area
                    'Category'
                                    Buildings
                                          Residential Buildings
                                          Religious Buildings
                                          Other Building
                                    Utilities
                                    Text/Toponym
                                    Road
                                    Rail
                                    Embankments
                                    Airport
                                    Boundaries
                                    Hypsography
                                    Hydrography
```

Canal

Hydro Associated

Coastal Features

Other Water Features

Vital Installations

Object region recognized by ANFIS has been returned.

Set transparency properties for objects in current axes.

'Thematic Map Generation'

'Road Map','Callback',{@layermg,var.Road}

'Contour Map','Callback',{@layermgc,var.Brown});

'River Map','Callback',{@layermg,var.River});

'Text/Toponym','Callback',{@layermg,var.Tex});

'Contour Surface','Callback',{@cntr,var.Contour});

Object region recognized by ANFIS has been returned.

Set transparency properties for objects in current axes

%end layerwise understanding

%Accuracy assessment of layer extraction

Compare ITMUS generated layer and manual delineated layer

Prompt user to select ROI from Topographic map.

Perfom Color code based layer segmentation.

Apply ROI descriptors to ANFIS.

Load GUI data with intermediate and object description.

Select Layers from interpred map

Plot ITMUS generated layer

%end Accuracy assessment

%end of MUS

# APPENDIX- II

## PENALTY MARTIX AND MISCLASSIFICATION COST

For the assessment of layer extraction shows that how much extent of objects or features in each layer is extracted correctly. The map layer extraction, assessment as discussed in [176] has been appropriate for overlay analysis of system generated layer and manually delineated layer to derive a penalty matrix. The value is estimated a misclassification result in terms of low, medium or high index. The details of the penalty matrix and cost of missclassification have been provided below:

### Error Measures

Cost Matrix is similar of confusion matrix. It's just, we are here more concerned about false positives and false negatives (shown below). There is no cost penalty associated with True Positive and True Negatives as they are correctly identified.

| | Predicted | | |
|---|---|---|---|
| Actual | | Positive | Negative |
| | Positive | 0 | C(FN) |
| | Negative | C(FP) | 0 |

Cost Matrix

The goal of this method is to choose a classifier with lowest total cost.

Total Cost = C(FN)xFN + C(FP)xFP

where,

1. FN is the number of positive observations wrongly predicted
2. FP is the number of negative examples wrongly predicted
3. C(FN) and C(FP) corresponds to the costs associated with False Negative and False Positive respectively. Remember, C(FN) > C(FP).

Let us introduce the error measures we used in building the analytics models for ITMUS. The "penalty error" is motivated by the fact that if we classify a very highly different class wrongly an another class, this is more costly than the reverse, namely classifying a class 1 as a class 5. Motivated by this, we developed a penalty error with the idea of using asymmetric penalties. The following figure show the *penalty error* as a matrix between outcome and (model) forecast.

For example, whenever while classifying a class 1 object as class 3, a penalty of 2 will be paid, which is a difference of 3 minus 1, the difference in the error. The off diagonal penalties are double the corresponding penalties in the lower diagonal. The class specification has been given below:

| | | Actual | | | | |
|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** | **5** |
| **Measured** | **1** | 0 | 2 | 4 | 6 | 8 |
| | **2** | 1 | 0 | 2 | 4 | 4 |
| | **3** | 2 | 1 | 0 | 2 | 6 |
| | **4** | 3 | 2 | 1 | 0 | 2 |
| | **5** | 4 | 3 | 2 | 1 | 0 |

Class 1: Utility

Class 2: Height

Class 3: Vegetation

Class 4: Man made

Class 5: Hydrography

**Missclassification cost**

| **Penalty** | **Low** | **Medium** | **High** |
|---|---|---|---|
| **Diagonal** | **pd<3** | **pd<=7** | **7< pd <=10** |
| **Off-diagonal** | **Po<9** | **9<Po <11** | **Po<11** |

Missclassification cost index is measured using penalty diagonal index and penalty off-diagonal index.

# APPENDIX- III

# List of Publications

## International journals:

1. Gitanjali G. Nikam, J. K. Ghosh (2015). Indian Topographical Map Symbols Understanding System, IET Computer Vision, The Institution of Engineering and Technology, pp. 1–9. DOI doi: 10.1049/iet-cvi.2013.0311.

2. Gitanjali G. Nikam, J. K. Ghosh (2013). Information extraction from topographic map using colour and shape analysis, Journal of the Indian Academy of Sciences, SADHANA, October 2014, Volume 39, Issue 5, pp. 1095-1117. DOI 10.1007/s12046-014-0270-5

3. Gitanjali G. Nikam, J. K. Ghosh (2012). Soft Computation Based Topographic Map Legend Understanding Prototype System, International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, Volume-3, Issue-1, March 2013, pp. 116-120.

## International conferences:

1. Gitanjali G. Nikam, J. K. Ghosh (2012). Indian Topographic Map Symbols Understanding System, Proceedings of the 2013 IEEE Second International Conference on Image Information Processing (ICIIP-2013), pp. 33-38.

2. Gitanjali G. Nikam, J. K. Ghosh (2012). A Map Legend Understanding Prototype System, Proceedings of International Conference on geospatial technologies and applications, Geomatrix'12, IIT Bombay, India, February 26-29, 2012, pp. 571-574.

3. Gitanjali G. Nikam, J.K.Ghosh (2011). A Map Legend Understanding System, Proceedings of the International Conference on Soft Computing for Problem Solving (SocProS 2011), IIT Roorkee, India, December 20-22, 2011, Vol. 131, No. 2, pp. 41-47. **Also, in** Advances in Intelligent and Soft Computing**,** Volume 131, 2012, pp 53-62. springerlink.com. DOI- 10.1007/978-81-322-0491-6_5

## Patent:

The authors are going to file a patent for the developed system (ITMUS).

# APPENDIX- IV

# APPENDIX- V

# Indian topographical map symbols understanding system

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**2 authors**, including:

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# Indian topographical map symbols understanding system

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**Abstract:** Symbol understanding is a pre-requisite for reading and interpretation of any map. Thus, any topographic map-based automated system needs to understand generic symbols associated with the set of maps. The objective of this study was to develop an automated system for the understanding of Survey of India topographic map symbols. The system has been developed making use of shape analysis adopting a complex-valued chain coding method for representation of the (exterior) boundary of the symbol. Fourier discrete transform and autocorrelation function have been used for shape descriptions. Classification and recognition have been implemented through a template matching method based on similarity measures. The system has been trained with 150 samples of 20 Indian topographic symbols and tested for 200 samples of each of the 20 symbols extracted from sample maps. Experimental results showed that the proposed method has an overall recognition rate of 84.68% as well as the improved mean average precision of symbol recognition. However, understanding of interconnected and/or crowded symbols may be taken up as future scope of this work.

## 1 Introduction

Map understanding involves a psychological process resulting in the abstraction of physical features such as geometrical entity, location or toponym to be used for further works. However, visual interpretation makes use of the symbols in the list of legends of the map for understanding. Nowadays, automated map understanding systems are being used for many applications such as map generalisation [1], matching of spatial datasets [2, 3], data fusion [4, 5] or data update [6, 7]. However, automatic map understanding can support data acquisition processes. Furthermore, map-making agencies like Survey of India (SOI) make use of a digitiser to convert paper-based maps into digital form and vector map data is created and maintained with manual tagging. There is also a need for automatic interpretation and tagging of raster maps. Thus, in an effort to develop an automated map understanding system, it is a prerequisite to develop a system that understands the representative map symbols.

Studies [8] have revealed that recognition of objects or symbols is primarily based on recognition of their outlines (shape). Thus, shape or exterior boundary provides the most distinguishing characteristics of an object or a symbol in spite of their differences in colour or texture. The objective of the study was to develop an Indian topographic map symbol understanding system to be used for automated reading of Indian topographic maps. In this work, issues related to shape description and computational methods for the interpretation of geometrical attributes have been investigated. Different sections of the manuscript have been organised as follows: Section 2 briefly describes a review of earlier works. In Section 3, the theory of shape analysis (SA), adopted in this study, is explained. Section 4 describes the methodology of the system developed, that is, the steps involved in symbol understanding as implemented in the system: image pre-processing, primitive recognition, template generation, template matching and understanding. Section 5 reports the experimental results. Section 6 describes the validation process. Section 7 discusses the result and system performance. Finally, Section 8 includes the conclusion of the study.

## 2 Previous works

Map understanding systems are usually based on pattern recognition using homogeneous parallel algorithms [9, 10], semi-automated recognition system [11] or query-driven recognition based on template matching [11–13]. Methods [14] adopted focus on the extraction of specific features such as points and lines etc. [15, 16]. The legend-driven map recognition systems make use of weighted classifiers which are noise sensitive and thus, make use of different layers as inputs, including layers based on colour features of scanned maps [17–20]. Many authors [21–25] suggested top–down approaches for recognition of symbols from maps and/or technical drawings.

Some systems have been reported in the literature which can recognise well-separated particular features and those which are present in different colours in the maps [26, 27]. Their recognition schemes rely on a heuristically chosen set of features but lack understanding of shape characteristics. A complex invariant feature representation between template matching and maximum pooling operation has been successfully implemented on a range of recognition tasks [2, 28, 29]. Acquisition, shape descriptions and retrieval of performance of different types of Fourier descriptors used have been demonstrated in [30].

Yang and Wang [28] proposed a three-stage system for recognition of multi-oriented Chinese character using features based on geometric measures of the foreground pixels of the characters. To segment text from engineering drawings, Adam *et al.* [31] used the Fourier–Mellin transform in a five-step process and made use of broken chains through heuristics.

Many contour matching methods [32, 33] were used for shape matching. These methods are primarily based on the extraction of features from the boundary and then matching the features to gauge the degree of similarity between the two shapes. Traditional approaches of overlaying were used for matching [34], which do not address the psychovisual approach for map understanding. Typically, a dynamic programming algorithm is used to preserve the ordering of features along the contour [35]. Many other systems [17–19, 26] consider the extraction of one or more types of features and primitives of complex maps but do not address the problems of symbols in different orientations.

SA methods can be classified according to many different criteria. Pavlidis [36] proposed that classification is based on the use of shape boundary points as opposed to the interior of the shape. The two resulting classes of algorithms are known as boundary (also called external) and global (or internal), respectively. Examples of the former class are algorithms that parse the shape boundary [37–44] and various Fourier transforms of the boundary [33, 45–50]. Shape perception provides collective understanding about the external/internal boundary and its shape, size and orientation. Furthermore, psychovisual system always uses the boundary/edge detection technique instead of threshold- or intensity-based measures for the recognition of different objects. Hence, edge detection is performed which itself is one of the segmentation techniques.

Most structural matching methods deal with graphical representations and string representations directly as in [36, 51], whereas template matching has to be carried out using cross-correlation and exhaustive search, that is, translating the template over every position in the search area [52]. Template matching provides an effective way of interpreting unknown samples by comparing them to a set of known prototypes or templates. Proper segmentation is a quite elaborate *ad hoc* procedure. However, no work has been reported on automated understanding of Indian topographic map symbols. Problems in extraction of features from topographic maps lie in their differential geometry and nature of interconnectedness among many features. A method based on the perception of shapes of symbols, which provides a collective understanding of size, form and orientation followed by orientation invariant similarity measures, is required for the development of an automatic topographic map symbol understanding system.

## 3 Background theory

### 3.1 Shape analysis

Shape representation and description are as important as pattern recognition methods. Efficient pattern recognition methods seek a well-instantiated outline representation scheme and shape descriptors. The outline of the symbol is a chain of points (pixels), separating it from a background. The boundary chain code describes the outline by a unit size segment with orientation. In this study, SA has been carried out using a complex-valued chain coding method and for representation of the (exterior) boundary of the symbol. The boundary has been detected through segmentation based on the canny edge detection technique. Edge segments with fixed length and slopes within different ranges have been proposed as primitives in describing symbols on a topographic map. Each vector of an outline is named as a primitive vector (PV) and a sequence of complex-valued numbers is designated as the template-outline vector (TOV). The orientation of symbols on certain angles is equivalent to each PV of an outline on the same angle. The starting point modification conducts to TOV cycle shift. As PVs are encoded concerning the previous point, a modification of the starting point will not change the sequence of a PV, but the first PV will be what begins at the starting point. Scale factor has been used to resize source symbol during detection process, if required. As a scalar product

$$\eta = (\Gamma, N) = \sum_{n=0}^{k-1} (\gamma_n, \upsilon_n) \tag{1}$$

where $k$ is the dimensionality of a TOV, $\gamma_n$ is the $n$th PV of outlines $\Gamma$, and $\nu_n$ is the $n$th PV of outline $N$. In SA, for the scalar product only PV of identical dimensionality is supposed. That is, the number of PVs in outlines should be the same. An illustration of complex-numbered chain coding representation of the outline is given in Fig. 1.

#### 3.1.1 Normalised scalar product:

In the proposed system, the multiplicative properties of normalised scalar product (NSP) have been used to provide a measure of closeness of vectors. If $\eta$ represents the NSP of two outlines from two different symbols, then $\eta$ has been defined [41] as

$$\eta = \frac{(\Gamma, N)}{|\Gamma||N|} \tag{2}$$

where the magnitude of $\Gamma$ and $N$, that is, the length of outlines is calculated as

$$|\Gamma| = \left(\sum_{n=0}^{k-1} |\gamma_n|^2\right)^{1/2} \text{ and } |N| = \left(\sum_{n=0}^{k-1} |\upsilon_n|^2\right)^{1/2} \tag{3}$$

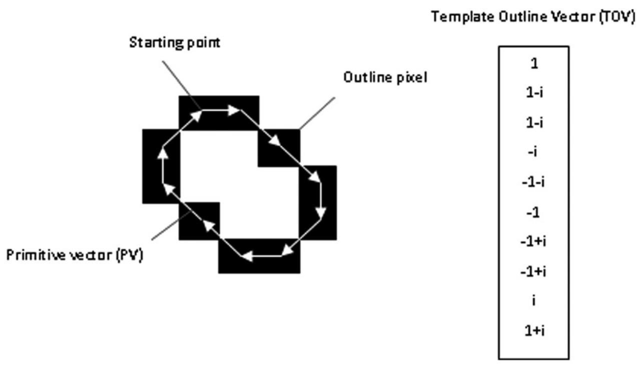


**Fig. 1** *Complex-numbered chain coding representation of outline pixels*



*IET Comput. Vis.*, pp. 1–9
doi: 10.1049/iet-cvi.2013.0311

**Table 1** Properties of the NSP of outlines

| | NSP | Re(NSP) = cos ($a$) | \|NSP\| |
|---|---|---|---|
|  | 1 | 1 | 1 |
|  | | | |
|  | $i$ | 0 | 1 |
|  | −1 | −1 | 1 |
|  | $-i$ | 0 | 1 |

The norm of the NSP has upper bound value as 1 if it is equal to the product of arbitrary complex number and PV of outline.

$$\Gamma = \mu N \tag{4}$$

where the size and orientation have been described by the arbitrary complex number $\mu$. Outline $\mu N$ means it is the same outline $N$, but scaled by a factor $\mu$. During multiplication, products have been computed for their lengths, and additions on arguments (i.e. angles). The magnitude of the NSP has been found to be 1 always, that is, for identical symbols having similar outlines but different orientations, that is, having different NSP vectors. A pictorial representation for four different orientations (0°, 90°, 180° and 270°) of the same symbols and their details of NSP vectors and their products depicting properties of the NSP are shown in Table 1. This has been implemented to make the system's performance invariant to the orientation of the symbols.

### 3.2 Similarity measure

Similarity measure has been used to determine the degree of similarity between two boundary vectors. In the current study, the similarity measure has been implemented as NSP [53, 54]. The norm of the NSP is calculated using (7) to find the maximum similarity between two outline vectors. Previously, the length or magnitude of query and original image, $|L(\Gamma,N)|$ is calculated using (5).

$$|\Gamma||N| = \left|L_{(\Gamma,N)}\right| = \left(\sum_{n=0}^{k-1}\left|\gamma_{(\Gamma,N)_n}\right|^2\right)^{1/2} \tag{5}$$

where

$$\gamma_{(\Gamma,N)_n} = \sum_{j=1}^{n}(f_j^q - f_j^i) \tag{6}$$

where $f_j^q$, $f_j^i$ are discrete Fourier descriptors of query and original images, respectively.

To make its starting point invariant, the similarity measure has been modified with an interrelation function (IF) which is defined as

$$\tau(m) = (\Gamma, N^{(m)}), \quad m = 0, \ldots, k-1 \tag{7}$$

where $N^{(m)}$ is the outline retrieved from $N$ by its PV on $m$ of elements. Thus, the modified similarity measure that has been used in this study is

$$\tau_{\max} = \max\left(\frac{\tau(m)}{|\Gamma||N|}\right) \tag{8}$$

$\tau_{\max}$ gives a measure of similarity of two outlines invariant to transposition, scaling, rotation and starting point shift and $\tau$ defines a degree of similarity of outlines, and becomes one of the similar outlines, and argument $\arg(\tau_{\max})$ shows an angle of orientation of one outline, with reference to another. The list produced is ranked using $\tau_{\max}$ which is used in template matching.

## 4 Methodology

The methodology consists of two broad steps: first, representation of pattern and second, matching of pattern. In this study, symbols are represented through the chain code technique, which is a flexible scheme for the representation and description of pattern images. Symbols are first segmented from their background. Then, through SA, these are represented through shape descriptors. In the present study, an external representation is used which focuses on a symbol shape outline feature using the spatial organisation of shape region, that is, the external space domain technique. Fourier discrete transform and autocorrelation function (AF) are used for shape descriptions. Classification and recognition are implemented through a template matching method based on similarity measures. Thus, the speed of the proposed method depends on the number of outlines/boundaries found in the map. Noise outlines generated in edge detection are minimised by applying the smoothing operator to the map. The outline, in this study, consists of a one-dimensional object. It is a vector of complex-valued numbers. For the generation of a good template, outlines from canny edge detection filter are processed further to make a continuous boundary or outline. This has been done before outline encoding. The proposed method pre-processes the map image to exhibit high contrast at the boundary and local adaptive thresholding is used for binarisation. Canny operator is used to detect boundary. Then, boundary tracing and approximation are carried out. Symbols or objects boundaries are searched for by a local analysis in finding shape starts from branch nodes and end nodes guided by heuristics. The shape is then encoded in a Freeman way, the $x$–$y$ offsets are used to obtain a complex representation of boundaries. The final matching of shapes is done by computing Fourier descriptors from the chain codes; comparison of descriptors is embedded in an NSP of descriptors.

A general overview of the functioning of the system in the training and testing phase has also been discussed as below.

The sequence of operations that have been undertaken during training consists of:

(i) Input of scanned image of Indian topographic map consisting of symbols to be trained.
(ii) Pre-processing of input image by smoothing, noise filtration and contrast enhancement.
(iii) Binarisation of pre-processed image and selection of outlines of symbols.
(iv) Filtration of the outlines and conversion to uniform length (Fig. 2).
(v) Searching of discovered outlines, generation of templates for symbols using pseudo code (using pseudo code as given in Fig. 4).

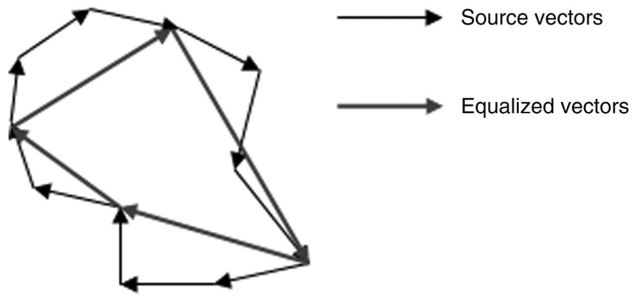


**Fig. 2** *Equalisation of TOV*

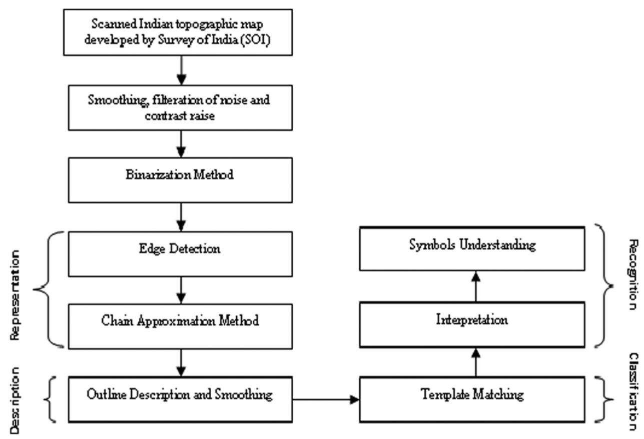


**Fig. 3** *Flow graph illustrating the main phases in the development of the topographic map symbol understanding system*

(vi) Designation of template for each of the discovered symbols.
(vii) Saving of templates of all discovered symbols along with designation.

Fig. 3 shows a flow graph of the proposed Indian topographic map symbol understanding system. The sequence of operations for testing of developed system consists of input, pre-processing, binarisation and filtration as done for training followed by searching of the template from training output which has maximum similarity with the template of testing input symbol. The output of the testing stage consists of interpreted symbols. The pseudo code for symbol searching is given in Fig. 4.

```
symbol = new Vector();
for each pixel do
if pixel.isEdgePixel() then stack.add(pixel);
shape = new Vector();
while ¬ stack.isEmpty() do
pixel = stack.pop()
shape.add(pixel)
stack.add(getNeighbours(pixel))
symbol.add(shape)
```

**Fig. 4** *Pseudo code for symbol searching*

### 4.1 Representation and description of symbol

The outlines of the symbols are encoded by a sequence of complex numbers. After detection, the outline of a symbol is read in the clockwise direction in terms of offsets starting from any point on the outline. Each offset vector is represented by a complex number $a + ib$, where $a$ is the point offset on the $x$-axis, and $b$ along the $y$-axis and stored with respect to the starting point for that particular offset. The sequences vary with the type of symbols and thus, characterise each symbol.

The algorithm for outline extraction and complex-valued chain code description is as follows:

Input: Digital Indian topographic map (Fig. 5*a*).
Steps:

1. To convert colour map image into a greyscale image (Fig. 5*b*).
2. To binarise image using local adaptive thresholding (Fig. 5*c*).
3. To extract the boundary or outline of the symbol using the canny edge detector (Fig. 5*c*).
4. To remove noise by applying, erode and dilate morphological operations (Fig. 5*d*).
5. To recognise the shape of symbol (using pseudo code as given in Fig. 4).
6. To trace the shape boundary in the clockwise direction and generate eight directional complex-valued chain codes from 1 to $1 + i$.
7. To compute frequency of the codes.
8. To divide frequency of each code by the sum of the frequencies.
9. To combine the values in steps 6 and 7 to obtain feature vector of the template.

Output: Complex-valued chain code of symbols.

*Feature vector:* Outlines of symbols have been designated by vector $\mathbf{\Gamma}$ which is defined as a function of $\gamma$ which are primary and basic vectors and thus, $\mathbf{\Gamma} = (\gamma_0, \gamma_1, \ldots, \gamma_{k-1})$. An operation over an outline of a symbol yields a vector of complex-valued code which has distinguished mathematical properties. The main motivation behind using a complex-valued chain is that it resembles two-dimensional coding where the outline is specified as a population of the PVs presented in the two-dimensional coordinate reference model. If TOV is increased by some scale, then the NSP will become 1 (see from (4)). The magnitude of the NSP of outlines becomes 1 in a situation when these two outlines are coinciding. Thus, the NSP has been used to search outlines from similar patterns, but vary with starting point selection for chain coding. Equation (6) is reached only if the starting point of outlines coincides. If outlines are identical, but the PV reference begins with another starting point, then the norm of the NSP of such outlines will not be equal to unity. Hence, the difference in successive direction, that is, inter-correlation, has been implemented as an interrelation factor (IF) $\tau_{\max}$. It gives a measure of similarity of outlines after changing the starting point on template to other positions.

The $\tau_{\max}$ has been found as a measure of similarity of two outlines. The magnitude defines a degree of similarity of lines, and becomes 1 for similar outlines, and argument arg ($\tau_{\max}$) shows an angle of orientation of one outline, with reference to another.




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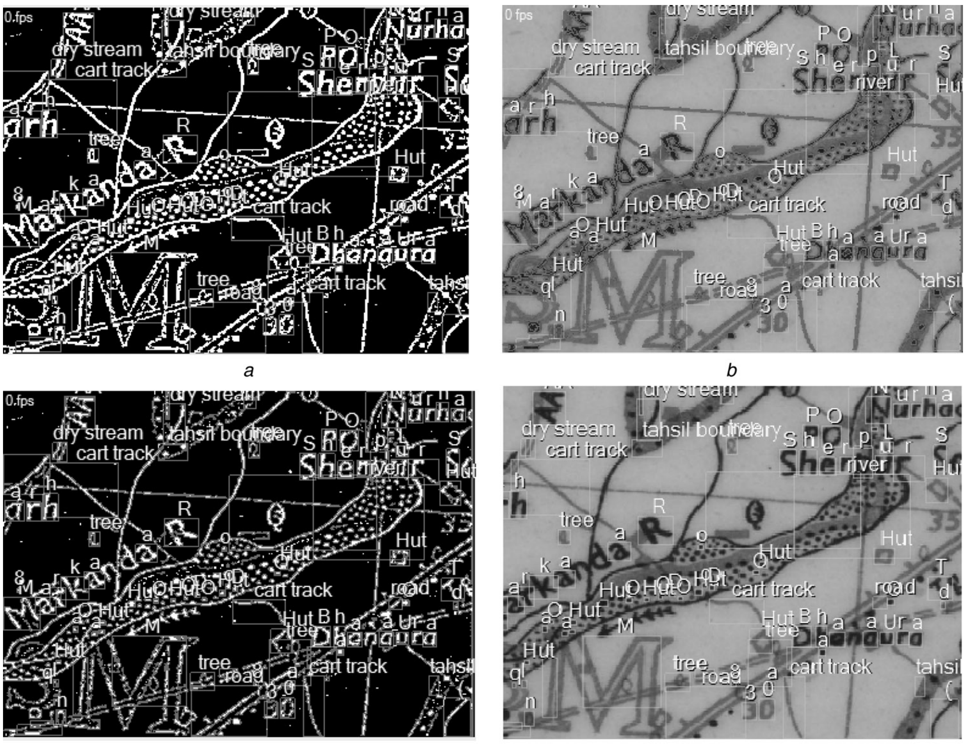


*a* *b* *c* *d*

**Fig. 5** *Representation and description of symbol*

*a* Greyscale form of a topographic map
*b* Binarisation of crop map image by local adaptive threshold, and the extraction of outlines by image processing routines
*c* Outlines are filtered using median filter
*d* Interpreted map

### 4.2 Autocorrelation function

In the present system, an AF is implemented and is always equal to IF (7) for which $N = \mathbf{\Gamma}$. It is a scalar product of an outline mostly on itself at various shifts of starting point, that is, $m$ is defined as follows

$$\nu(m) = \left(\mathbf{\Gamma}, \mathbf{\Gamma}^{(m)}\right), \quad m = 0, \ldots, k-1 \tag{9}$$

The AF does not depend on a choice of starting point of an outline. If the outline has any symmetry, then its AF has similar symmetry. The norm of an AF is symmetric concerning a central reference $k/2$, where $k$ is the dimension of TOV. As the AF is the total of pairwise product of a PV of an outline, each pair meets two times at an interval from 0 to $k$. Consider the graphics AF for some outlines as in Fig. 6. The norm the AF is represented by histogram (an AF it is represented only for an interval from 0 to $k/2$). An outline AF is implemented as characteristic descriptions of the shape of an outline. The template and corresponding AF for some outlines are shown in Fig. 6. From the boundary trace of the shape, a series of complex numbers are generated. If $N$ samples of a closed $\mathbf{\Gamma}$ are taken, then it is defined by

$$u(n) \triangleq x(n) + jy(n), \quad n = 0, 1, \ldots, N-1 \tag{10}$$

Its discrete Fourier transform (DFT) is represented as follows

$$f(k) \triangleq \sum_{n=0}^{N-1} u(n) \exp\left(\frac{-\mathrm{j}2\pi kn}{N}\right), 0 \le k \le N-1 \tag{11}$$

DFTs which act as descriptors for a series of complex-valued chain codes have been calculated using (10) and (11) given above.

### 4.3 Template matching

After extracting the shape of a symbol, the next step is to match it against a set of template models. However, because of different orientations and interconnectedness within the topographic map, variation within the same type

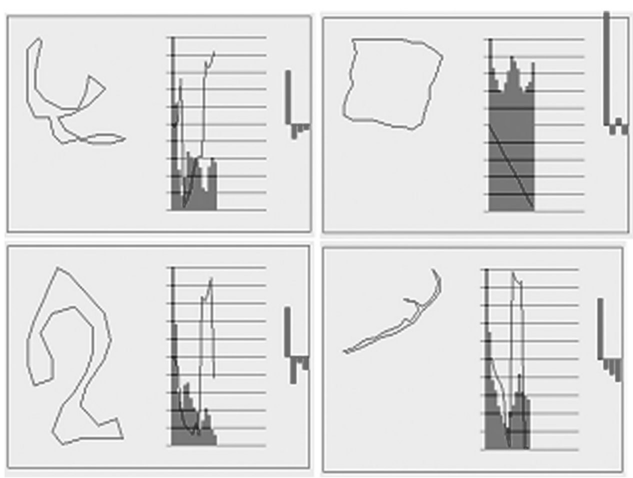

**Fig. 6** *Outlines are equalised and AF descriptors are calculated which are used to find a template which matches with the template most similar to the template pattern discovered*

**Table 2** Recognition rate for symbols in Indian topographic map

| Symbols | 5-fold cross-validation | | | | | Overall recognition |
|---|---|---|---|---|---|---|
| | Fold-1 | Fold-2 | Fold-3 | Fold-4 | Fold-5 | |
| hut | 87.90 | 93.04 | 82.30 | 82.67 | 86.00 | 86.38 |
| tree | 100.00 | 92.89 | 96.03 | 100.00 | 100.00 | 97.78 |
| grass | 90.83 | 92.90 | 89.00 | 91.45 | 91.58 | 91.15 |
| antiquities | 92.56 | 100.00 | 100.00 | 93.01 | 92.85 | 95.68 |
| road | 86.90 | 92.90 | 90.54 | 82.00 | 91.78 | 88.82 |
| dry stream | 90.76 | 90.70 | 89.87 | 91.98 | 87.99 | 90.26 |
| cart-track | 89.87 | 90.77 | 91.45 | 92.78 | 89.02 | 90.77 |
| river | 90.67 | 88.43 | 91.32 | 90.70 | 87.90 | 89.80 |
| broken land | 92.30 | 90.54 | 92.89 | 96.03 | 100.00 | 94.35 |
| well | 89.02 | 82.67 | 89.00 | 86.90 | 89.87 | 87.49 |
| Tahsil boundary | 82.66 | 78.90 | 81.78 | 91.78 | 89.00 | 84.82 |
| canal | 91.45 | 89.00 | 89.17 | 85.90 | 87.99 | 84.82 |
| dams | 87.90 | 86.34 | 92.90 | 90.54 | 88.00 | 89.13 |
| tube well | 86.90 | 89.97 | 89.00 | 82.30 | 86.15 | 86.86 |
| temple | 91.90 | 92.89 | 92.89 | 90.67 | 91.00 | 91.86 |
| fort | 92.60 | 88.43 | 89.87 | 93.02 | 91.45 | 91.07 |
| Church | 88.90 | 87.00 | 92.30 | 91.11 | 88.92 | 89.64 |
| river with rock | 72.67 | 80.05 | 78.45 | 75.00 | 76.01 | 76.43 |
| tanks | 86.90 | 83.67 | 81.78 | 86.90 | 82.30 | 84.31 |
| tower | 88.78 | 87.05 | 86.90 | 85.56 | 86.90 | 87.03 |
| overall recognition rate | 89.07 | 88.90 | 89.37 | 89.02 | 89.23 | 84.68 |

is not uncommon. In this approach, correlation measure is used to measure the match. For digitised images, which are encoded with $\Gamma$ and $N$, the normalised cross-correlation as a measure of a match is defined by the NSP and given by (2), (4) and (5). Then, the fast Fourier transform (as given by (11)) is used to calculate the NSP, that is, shape descriptor.

The template matching algorithm is implemented as follows:
Input: Set of templates; testing map image.
Output: Matched primitives
Steps:

1. Load the set of templates in $T$.
2. Extract the shape of test object $C$.
3. Initialise the level of similarity of primitive $\tau$ to be 1.
4. Let $S$ be candidate set and $S$ = primitive ($\tau$, $C$)
5. Let $M$ be the match set and $M$ = Match ($T$, $S$)
6. If $M$ is not empty return $M$. Otherwise $\tau = \tau + 1$.
7. If $\tau$ is less than or equal to the maximum primitive level then go to step 4. In another case exit.

## 5 Experimental results

The developed system has been trained and tested for 20 symbols. The training and testing datasets contain, respectively, 150 and 200 samples for each of the symbols. Topographic images with sizes of $350 \times 300$, $800 \times 600$, $1500 \times 400$ and $2700 \times 2900$ at 300 dpi have been considered for both training and testing. The system has been trained and tested in a grid of $50 \times 50$ within each of input sample images implementing the methodology, as described in Section 4. For testing, the sample images have been grouped into 5-fold cross-validation. The trained models have been used to recognise symbols found in input topographic images having an overall success rate of 84.68%. It was found that tree, antiquities, broken land and grass have higher recognition rates as compared with 16 other symbols. The errors in recognition for hut, road and river were found to be higher than other symbols. The testing result is shown in Table 2.

The percentages of correct recognitions achieved by using the templates are also drawn from five test images of size $600 \times 600$ pixels. There are 79 occurrences on the images for symbol Hut, 9 for symbol Tube well and 20 for symbol Tree. To evaluate the performance of the method with respect to other techniques, the same test was carried out on different topographic maps of the same size with templates drawn according to the matched filtering approach. The recognition rates obtained and the average times employed in the matching phase by the two methods on the test images are presented in Table 3, together with the sizes of the templates. We tested the same symbol sets for matching filtering along with turning function which is employed by Siyu *et al*. Examination of Table 3 shows that the proposed method seems to be practically slightly better than the matched filtering technique regarding the recognition rate, while the processing time is significantly reduced. This speed-up depends on two factors. First, the reduction of the number of pixels in the template reduces the operations

**Table 3** Performance of the proposed method compared with the matched filtering technique

| Symbol | Proposed method | | | Matched filtering with turning function | | |
|---|---|---|---|---|---|---|
| | Percentage recognised | Time | Size | Percentage recognised | Time | Size |
| hut | 96.64 | 10.54 | 94 | 95.10 | 76.53 | 120 |
| tube well | 98.82 | 13.26 | 416 | 96.63 | 96.12 | 489 |
| tree | 95.93 | 11.50 | 183 | 94.12 | 80.25 | 197 |

Time represent the average times (in seconds) necessary to process a $600 \times 600$ pixels image



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**Table 4** Performance of the proposed method compared with the system developed by Zhu *et al.* [55]

| | Rotation variant | Classifier | Dataset | Recognition rate |
|---|---|---|---|---|
| proposed system | inter-relation function AF | template matching | NTDB by SOI | 97.13 |
| Zhu *et al.* [55] | turning function | nearest neighbour algorithm | Infty CDB-30 | 96.90 |

needed and second, the use of only complex numbers in the template instead of real numbers greatly reduces the computational load.

## 6 Validation

The performance of the same topographic map interpretation system has been tested on USGC and other cartographic map databases which are not available to others. The performance of the developed system is compared with the symbol recognition system developed by Zhu *et al*. [55]. The experiment results show that inter-correlation function with normalisation and autocorrelation perform the best. The recognition rate of 97.13 is obtained for a restricted dataset which is mentioned in the previous paragraph. It is shown in Table 4. The experimentation is carried out without cross-validation. The effectiveness of our system has also been tested for the National Topographic Database (NTDB) developed by the SOI. The samples consist of 20 symbols containing 3000 samples. Also, the performance and accuracy of the system in pattern retrival is computed using the precision and recall metric. These metrics are further used to plot the precision–recall curve and receiver operating characteristics (ROC) curve which in turn were used to compare the result with the above-mentioned system which is developed by Siyu *et al*.

**Table 5** Contingency table for accuracy assessment

| | Relevant/correct | Not relevant/not correct |
|---|---|---|
| recognised | *w*: TR (2608); TS (2360) {TP-Hit} | *y*: TR (68); TS (312) {FP} type-I error |
| not recognised | *x*: TR (74); TS (140) {FN-Miss} Type-II Error | *z*: TR (250); TS (188) {TN-Correct Rejection} |

TR, for training samples, TS, for testing samples

### 6.1 Evaluation metrics

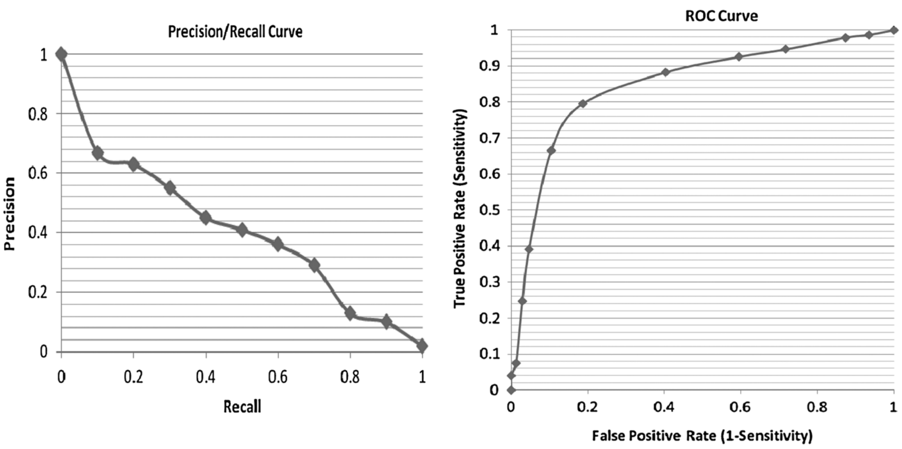
An important criterion for testing the efficiency of the search and retrieval is that the output must include all of the similar images [41]. The list produced is ranked using $\tau_{\max}$. The performance of retrieval is:

Recall (for training samples, TR) $= w/n_1 = 0.9724$ and recall (for testing samples, TS) $= w/n_1 = 0.944$, where $n_1$ is equal to $w + x$. Here, $x$ is relevant but not recognised symbol.

Precision (for training samples, TR) $= w/n_2 = 0.9745$ and precision (for testing samples, TS) $= w/n_2 = 0.8832$, where $n_2$ is equal to $w + y$. Here, $y$ is recognised but not relevant symbol. Table 5 describes the evaluation metrics of the proposed system for symbols.

Overall percentage accuracy, that is, $w/N$ (for both training and testing samples) has been calculated by $= (4968/5406) *100 = 91.89\%$.

For the retrieval experiment, we use the five toposheets from NTDB as the candidate library and 52 queries in testing toposheet image. Marinai *et al*. use the whole InftyCDB-3 as the candidate library, for 392 queries. Siyu *et al*. use the InftyCDB-3 as the candidate library and 393 queries. The whole retrieval experiment for 52 symbols instances takes 144 s. To evaluate the average performance of the proposed system, we plot the precision–recall curve and ROC curve in Figs. 7*a* and *b*, respectively. In ROC space, we plot the false positive rate (FPR) and true positive rate (TPR) on *x*- and *y*-axis, respectively. The FPR measures the fraction of negative templates that are misclassified as positive. The TPR measures the fraction of positive templates that are correctly labelled. The FPR, TPR and area under curve (AUC) are given in Table 6. In the precision/recall space, we




*a* *b*

**Fig. 7** *Average performance of the proposed system using precision-recall curve and ROC curve*

*a* Precision–recall curve
*b* ROC curve


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**Table 6** False positive rate, true positive rate and area under curve

| FPR | TPR | AUC |
|---|---|---|
| 1 | 1 | 0.065089 |
| 0.934911 | 0.98659 | 0.081729 |
| 0.873452 | 0.978927 | 0.133227 |
| 0.715976 | 0.94636 | 0.114795 |
| 0.594675 | 0.925287 | 0.17794 |
| 0.402367 | 0.882261 | 0.175429 |
| 0.186391 | 0.795402 | 0.043205 |
| 0.104206 | 0.665136 | 0.038456 |
| 0.046213 | 0.390805 | 0.010406 |
| 0.028851 | 0.247126 | 0.004387 |
| 0.011834 | 0.074714 | 0.000884 |
| 0 | 0.04023 | 0 |
| 0 | 0 | 0 |
| | | 0.845547 |

**Table 7** MAP and AUC of ROC and precision–recall curve

| | MAP, % | AUC |
|---|---|---|
| proposed system | 7.92 | 0.8455 (ROC)<br>0.5107 (p/r) |
| Zhu *et al.* [55] | 6.43 | 0.4727 (p/r) |

plot recall and precision on the *x*- and *y*-axis, respectively. Recall is equivalent to TPR, whereas precision measures the fraction of templates classified as positive that are truly positive. In other words, precision measures the positive recognition of fraction of templates that are truly relevant. The AUC of the precision–recall curve is calculated by a piecewise explicit integration along the recall values. Mean average precision (MAP), and AUC of ROC and AUC of the precision–recall curve are given in Table 7. Marinai's shape context-based method achieved (33.13%) AUC and Siyu's nearest neighbour-based method achieved (47.27%) AUC [55]. Our AUC for precision–recall curve and for ROC curve is 51.07 and 85.55%, respectively. Higher AUC indicates that the system performs better.

## 7 Discussion

The main motivation behind using a complex-valued chain is that it resembles two-dimensional coding where the outline is specified as a population of the PVs presented in the two-dimensional coordinate reference model. If TOV is increased by some scale, then the NSP will become 1 (see (4)). The magnitude of the NSP of outlines becomes 1 in a situation when these two outlines are coinciding. Thus, the NSP has been used to search outlines from similar patterns, but vary with starting point selection for chain coding. Equation (6) is reached only if the starting point of outlines coincides. If outlines are identical, but the PV reference begins with an other starting point, then the norm of the NSP of such outlines will not be equal to a unity. Hence, the difference in successive direction, that is, inter-correlation has been implemented as an interrelation factor (IF) $\tau_{\max}$. It gives a measure of similarity of outlines after changing the starting point on the template to other positions.

The chain approximation algorithm results in external spatial representation of symbols. The template generator creates a template for each symbol and computes AF descriptor for the matching process. As an AF descriptor (represented by sky blue colour) values (see Fig. 6) distributed and represented only for an interval from 0 to $k/2$, it is clear that if the exterior boundary has symmetry then its AF leads to symmetry. Here, $k$ is the dimension of TOV. The AF value of Hut symmetrical and matches with many anti-pattern as well as template generated from small dot. So, the main power, tele-ines, dry wells on topographic map recognised incorrectly as Hut or vice versa. Also, road, river, cart-track and many such objects whose shape cannot be defined by distinctive boundary always lead in incorrect recognising. All these are the line features represented by irregular shape and size but distinct colour. Template matching method gives results with maximum matches of AF. Hence, even the system is inductively trained for cart-track gives it as dry stream. For such objects recognition rate is below 90%. As understanding is based on connected features, symbols are touching with other symbols or letters and numbers yield misinterpretation. The learnt template patterns are stored in the binary model stored in file with .bin extension.

## 8 Conclusion

Topographic map provides valuable information to a planner or surveyors, but their understanding remains a time-consuming and subjective task. The SA method used in the system provides a new representation and a description paradigm for map symbol interpretation and understanding. Structural approach using a string scheme applied to pre-processed map provides a flexible scheme to represent and describe shapes of boundary outlines using complex-valued chain coding. The shape encoding has been constructed to consider orientation and starting point selection criteria. Also, inter-correlation function and AF are implemented for searching outlines similar among themselves and to overcome difficulties with the NSP. Template matching has been implemented based on similarity measure which is having less computational complexity. Testing method of system yields 84.68% recognition rate of the symbols of an Indian topographic map. Also, accuracy of retrieval is 91.89%. Although the performance of the Indian topographic map symbol understanding system described here is promising, the fully automatic understanding of topographic maps remains an open problem because of the complexity, wide variability of the characteristics and heavily interconnected objects and labels and different features of topographic maps. The future scope of the study will be to address the specified problems.

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# Information extraction from topographic map using colour and shape analysis

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**Abstract.** The work presented in this paper is related to symbols and toponym understanding with application to scanned Indian topographic maps. The proposed algorithm deals with colour layer separation of enhanced topographic map using k-means colour segmentation followed by outline detection and chaining, respectively. Outline detection is performed through linear filtering using canny edge detector. Outline is then encoded in a Freeman way, the x-y offsets have been used to obtain a complex representation of outlines. Final matching of shapes is done by computing Fourier descriptors from the chain-codes; comparison of descriptors having same colour index is embedded in a normalized scalar product of descriptors. As this matching process is not rotation invariant (starting point selection), an interrelation function has been proposed to make the method shifting invariant. The recognition rates of symbols, letters and numbers are 84.68, 91.73 and 92.19%, respectively. The core contribution is dedicated to a shape analysis method based on contouring and Fourier descriptors. To improve recognition rate, obtaining most optimal segmentation solution for complex topographic map will be the future scope of work.

**Keywords.** Colour segmentation; shape analysis; outline detection; chain coding; template matching.

## 1. Introduction

Scanning of topographic map provides a comprehensive digital repository of topographic maps developed by Survey of India (SOI), but it is not in computer understandable format. Government and agencies capture digital information or convert existing analogous map information. For instance, maps available in a vectorized format and organized in layers are often insufficient to recognize geographical objects relevant for a certain application. This deficiency is even more evident for patterns of geographical objects interesting for geographers, geologists and

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town planners. Beside the task of solving spatial problems, automatic map understanding can be used to support other applications, like map generalization (Zhang 2009), spatial datasets matching (Volz & Walter 2006; Butenuth *et al*. 2007; Chen & Walter 2009), data fusion (Wiemann & Bernard 2010; Anders & Fritsch 1996) or data update (Walter 2004; Malerba *et al*. 2003). Furthermore, automatic map understanding can support data acquisition processes or used to form valuable set of information for large scale map analysis. Therefore, it is an interesting scope for an automated understanding of map to automate the extraction of information from unintelligent raster topographic map. The study is based on the assumption that the map understanding process typically follows computer vision technique driven by intelligent method that deciphers objects based on similarity criteria. The objective of this paper is to explain system development for understanding symbols, letters and numbers from scanned topographic map by applying shape description scheme to determine the interconnected trends and patterns and to find templates based on similarity criteria. Shape representation and description scheme with auto and inter correlation functions which are invariant to size and orientation is proposed. Our earlier work on legend understanding (Nikam & Ghosh 2012) discusses FFBN architecture for structure primitives' recognition. However, the issues like orientation of symbols and highly interconnected nature of topographic map come into picture while building the complete integrated solution for map understanding which is not addressed in our earlier work. In this paper, complete solution that can understand symbols, letters and numbers appearing on a map is presented. Two main issues raised out of that initial work are the choice of an appropriate set of features to be used for the symbol representation or description along with colour as it is most dominant and distinguishing feature in raster map and the definition of computational methods for their interpretation. In this work, we investigate these two issues, i.e., symbol description and computational methods for the interpretation of geometrical attribute like colour and shape feature. Psychological studies (Biederman & Ju 1988) prove that humans can recognize object using just the outline (shape) which carries characteristic information about it. A symbol is an essential component of a topographic map and its recognition based on its shape, is important in map understanding system. Also, letters and numbers on topographic maps provide additional information about the terrain. Contribution from this paper includes topographic map symbol and character understanding based on shape analysis and template matching technique.

Section 2 briefly reviews earlier work, while section 3 describes colour segmentation method applied. Section 4 gives detailed description of shape analysis techniques and similarity measures which are used for template matching. In section 5, the methodology used for creating the understanding, image pre-processing, primitive recognition, template generation and matching are described. Section 6 reports the experimental results. Finally, section 7 includes conclusion.

## 2. Review of earlier work

The work of map understanding started with a cartographic pattern recognition system using homogeneous parallel algorithms (Starr 1984; Ejiri *et al*. 1984), automatic map recognition system (Kasturi & Alimony 1988) and query-driven map recognition based on template matching (Yamada *et al*. 1997). The method (Samet & Soffer 1994) focused on extracting specific features such as points and lines based on a computationally intensive multi-angled parallelism method, whereas (Samet & Soffer 1996, 1998) reported a legend driven map recognition system. It relies on weight bounded nearest-neighbour classifier that is noise sensitive and needs separate map layers as inputs. Due to the large variety of the available feature extraction methods

(Trier *et al*. 1996; Heutte *et al*. 1993) many researchers have turned towards the use of several feature extractors with more complex structures of classification. The set of features (either statistical or structural) describing a pattern must be constrained to map the feature vector. This mapping consists in a parameterization of each feature, i.e., defining numerical parameters for each feature (Graeff & Carosio 2002). Most often, the parameterization of such features is obtained using a zoning-like technique (Heutte *et al*. 1993): a fixed n X m grid is superimposed on the pattern image and the feature is searched in each of the n X m regions, thus giving a binary feature vector of length n X m. Unfortunately, this results in a loss of data on the feature position additionally on a loss of continuity within the parameter area. An approach for the automatic interpretation of scanned topographic maps with query languages can be found in (Viglino & Pierrot-Deseilligny 2003). In this, the interpretation is done with pattern recognition algorithms in the raster domain. The detected objects are implicitly contained in the raster images but were explicitly modelled when the corresponding analogue map was produced. Therefore, the objects are already visible, but cannot be queried because of the raster representation. A combination of a raster- and vector-based approach is discussed in (Viglino & Pierrot-Deseilligny 2003). The input for this process is a raster map that is converted into a vector representation. Different object classes (for example buildings, hangars or parcels) are reconstructed with low level primitive extraction and subsequent classification. Spatial data mining approaches are reported in (Heinzle & Sester 2004). They describe the automatic extraction of classical metadata from spatial data sets and concepts of information retrieval to derive implicit information with data mining algorithms. Heinzle *et al*. (2007) continued their work and developed an algorithm for the automatic recognition of patterns in road network. The search for patterns in maps in order to detect implicit information for the automatic map generalization is described in (Mackaness & Edwards 2002). They argue that any map can be seen as a subset of possible patterns and a map generalization is a set of transformations from one pattern to another. An ontology driven pattern recognition approach for the detection of terraced houses in vector data is presented in (Luscher *et al*. 2008). They use ontologies to describe the characteristics of terraced houses and map this ontology onto a pattern recognition process. Steinhauer *et al*. (2001) present a method for recognition of abstract regions in a map. An abstract region consists of several map objects, which are grouped to a single object. The process is subdivided into two steps. First, region candidates are selected based on an evaluation of neighbourhood relations. Then, objects which consist of a hierarchical combination of single objects are recognized with a grammar-based compiler approach. Automatic sketch interpretation is a problem which has many similarities to the problem of automatic map interpretation (Wuersch & Egenhofer 2008). However, in sketch interpretation the main focus is more on segmentation, classification and labelling (Sezgin & Davis 2005), whereas in map interpretation the focus is more on the following tasks, like segmentation or data mining. Maps consist typically of well-formed geometrical objects whereas sketches could also be represented by very simple geometrical entities. Nevertheless, both research areas have a large overlap. Different map objects have typical geometrical appearances depending on their object type. For example: houses have typically rectangular structures, rivers are normally represented with smooth lines and streets are often represented with straight lines. Some objects have a very typical unique appearance, like churches. In order to interpret the object type, the objects can be represented with a feature vector, which consists of different geometrical measures, and then classified with an unsupervised or supervised classification algorithm. Complex objects can also be interpreted with model-based approaches. Weindorf (2002) proposed an approach that is based on a grammatical description of objects. The model is represented with grammatical rules in PROLOG (Logic Programming Language). The inputs are geometrical primitives (lines and text elements) which are grouped together by interpreting the grammatical rules. A graph-based approach for detecting geometrical structures in road networks is described in (Heinzle *et al*. 2005, 2007). The patterns (e.g., grids, stars and rings) are used for automatic determination of city centers in vector maps. Top-down approaches are suggested to be especially suitable for recognizing symbols or letters from maps or technical drawings in (Ventura & Schettini 1994; Myers *et al*. 1996; Den Hartog *et al*. 1996; Reiher *et al*. 1996). As paper focuses on understanding the pattern of symbols, letters and numbers from topographic map, we have reported research work which is done in recognition and interpretation of pattern. Traditional approach of overlying used for matching (Ebi *et al*. 1994) generates lots of false positives in interpretation. Research has also been done by separating the layers of scanned maps by colours as in (Roy *et al*. 2007; Dhar & Chanda 2006; Chaing *et al*. 2005; Khotanzad & Zink 2003). Other systems as reported in (Chaing *et al*. 2005; Khotanzad & Zink 2003; Gamba & Mecocci 1999; Wiskott & Malsburg 1993), mostly consider the extraction of one or more types of features and primitives from maps but do not address the problems of symbols, non-horizontal text or character. Due to the problems in the extraction of features from topographic maps i.e. differential geometry and highly interconnected nature of many features, many of the systems reported in the literature have focused on maps where features are well-separated from each other or printed in separate colours (Gamba & Mecocci 1999; Wiskott & Malsburg 1993). These recognition schemes relied on a heuristically chosen set of features. Lam & Suen (1988) developed a method for the recognition of handwritten numbers using structural classifier and recognition algorithm. Significant works on well-separated character recognition in the past two decades include the multi-font character recognition scheme and direction specific spatial features with structural configuration scheme (Pavlidis 1980; Kimura & Shridhar 1991). Chen & Lieh (1990) developed a two-layer random graph based scheme containing components and strokes as primitives and variation which is further encoded in the random graphs. Gader *et al*. (1991) developed template and a model matching model in two stage recognition system. Kjersti *et al*. (1995) developed a Hidden Markov Model for text recognition from gray level images but failed to handle problems of invariance to scale and font. Extended freeman's chain encoding schemes (Chan & Yeung 1999) have been used to extract feature primitives of numbers and letters but suffers from directional ambiguity. Chan & Yeung (1999) used Shape's primitive and Freeman's chain code to recognize handwritten alphanumeric characters. No work on recognition and understanding of labels in the raster topographic map has been reported so far in the literature. A method based on perception of shape i.e., outline or boundary of symbol which provides a collective understanding of size, form and orientation is required towards development of a topographic map understanding system. To cope with the above mentioned problems, authors have decided to normalize the structural features by continuous numerical variables, such as the 'X–Y position' of exterior outline or external outline. Indeed, these variables are calculated relative to the direction of freeman chain code of the shape and normalized in complex chain code according to the width or the height of the pattern bounding box in the form of template. This allows to locate accurately the structural features and to respect the principle of continuity. Thus, main objective of this paper is to describe an algorithm which is simple and straightforward that allows efficient representation or description scheme for faster matching that is based on similarity measures.

## 3. Colour segmentation

The instinctive and normal approach to layer separation problem is to apply the R, G, B pixel values for classification. However, a direct segmentation approach is not suitable for topographic map segmentation due to broad variations in colour intensity. For example, the green component of red pixel may be more than the green component of green pixel in the same map. Secondly, as *a priori* probabilities of pixels in different layers are not comparable, the cluster corresponding to the dominant layer tends to invade the other layers.

Another difficulty is that the intensity values of black or white pixels rarely have the ideal values of (0, 0, 0) or (255, 255, 255) and such pixels tend to be wrongly classified. Because of the above difficulties, the strategy devised for colour segmentation first determines the initial cluster centers on the basis of an enhanced image, followed by the separation. Dhar & Chanda (2006) have carried out layer separation by advanced k means algorithm and then recognition is performed in each layer separately. In our approach, we have adopted the same method only to separate layers and to find colour which will be used as a key to search the template which is most similar to the test symbol templates. Here, recognition does not require separate layers to interpret the symbols or toponym. The steps involved in our approach are as given below.

### 3.1 *Image enhancement*

The training image is enhanced such that the R, G, B values of the pixels are either 0 or 255. The heuristic or available alternatives are as follows. Pixels with a small difference in their R, G, B values are set to either fully black (0, 0, 0) or fully white (255, 255, 255) depending upon the average intensity value. Otherwise the maximum of the three values is set to 255 and others to 0. So we have the following classes to represent layers: $C_0 = \{0, 0, 0\}$, $C_1 = \{255, 0, 0\}$, $C_2 = \{0, 255, 0\}$, $C_3 = \{0, 0, 255\}$ and $C_4 = \{255, 255, 255\}$for black, red, green, blue and white, respectively. If two values are same and the maximal, both of them are set to 255. So we have three additional classes to represent layers: $C_5 = \{255, 255, 0\}$, $C_6 = \{0, 255, 255\}$, $C_7 = \{255, 0, 255\}$ for yellow, cyan and magenta, respectively. However, since in our present experiment, selected maps do not have any such colour layers, any pixel satisfying one of these is mapped to one of $Ci$ ($i = 0, 1, \ldots, 4$) depending on the intensity over its neighbourhood. This allows us to deal with only five classes.

Clusters are group of same colour pixels and so are layers. Here five clusters (black, white, red, and green and blue) result five layers. As white colour cannot be assigned for foreground colour object, four layers are considered for finding symbol. Whatever symbols recognized are the combination of these colours only. (Here, combination does not mean the mixing of RGB; it means single colour, two colour or multi colour objects or symbols). Example, river with rock is two colour symbols. Blue colour is assigned for river or water feature and black colour is for rock or sand in river bed. Our algorithm successfully finds two templates one for water and one for rocks with different colour index i.e., two sub-templates from two layers for same object. Also template generated for river is different from river carrying rocks. Thus, template matching algorithm searches a template with blue colour index in which it finds two templates (we are saying it as two only to illustrate the concept) and then matching is performed with the template found in testing image to determine its type i.e., whether it is river or river with rock.

In this paper, initial image enhancement process is done for determining the initial positions of the centroids of the clusters. K-means algorithm is applied to separate final clusters/layers. Apart from these 5 primary clusters/layers we may also require to separate some secondary layers (yellow, cyan and magenta) and these 8 give us almost complete description of the map. But as said earlier, it is not required in current maps which are under study.

### 3.2 *Segmentation*

The K-means algorithm (Chanda & Dutta Majumdar 2000) is used to generate $K = 5$ clusters, where each pixel of the original image is allocated to one of the five clusters such that the intra-class distance is minimum. The feature vector is selected to be the normalized original R, G, B values, along $r_i = \frac{R_i}{R_i+G_i+B_i}$; $g_i = \frac{G_i}{R_i+G_i+B_i}$; $b_i = \frac{B_i}{R_i+G_i+B_i}$; $I_i = \frac{R_i+G_i+B_i}{3\times 255}$ with the normalized intensity $I$ ('$I$ ' was added as a component of the feature vector in order to differentiate between the black and white clusters, as their normalized $\{r_i, g_i, b_i\}$ values tended to be similar) as follows: The initial cluster centers are supplied as the average of the normalized components $(r_j, g_j, b_j, I_j)$ of the pixels corresponding to each of the $Cj$'s of the enhanced image, where $r_j = \frac{1}{n_j}\sum_{i\in C_j} r_i$, $g_j = \frac{1}{n_j}\sum_{i\in C_j} g_i$, $b_j = \frac{1}{n_j}\sum_{i\in C_j} b_i$ and $I_j, = \frac{1}{n_j}\sum_{i\in C_j} I_i$, where $n_j$ is the total number of points in class or group $C_j$ of the enhanced image. K-means segmentation treats each symbol or any foreground object as having a location in space (Dhar & Chanda 2006). We found partitions such that objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. K-means segmentation requires that distance metric to quantify how close two objects are to each other. For every object in topographic map input, k-means returns a value corresponding to a cluster. The output from k-means will be used in the template matching.

Once the final cluster centers are determined, the map image is separated into the desired layers. Cluster index is stored in binary file. Templates generated using shape analysis and their respective cluster indices are stored as colour indices in binary file. Colour index helps to narrow down the search space for template matching. For example, if green object is recognized then its contour is matched against templates which are stored with their colour index corresponding to green layer.

## 4. Shape analysis

Shape analysis methods can be classified according to many different criteria. The first criterion is based on the use of shape boundary points as opposed to the interior of the shape. The two resulting classes of algorithms are known as boundary also called external or internal. Many studies are reported to parse the shape boundary (Nevatia 1982; Goshtasby 1985; Davis 1986; Kartikeyan & Sarkar 1989; Taza & Suen 1989) and various Fourier transforms of the boundary (Zahn & Roskies 1972; Granlund 1972; Richards & Hemami 1974; Persoon & Fu 1977; Wallace & Wintz 1980).

Topographic map understanding typically involve two steps: feature extraction in which the patterns are represented by a set of features and classification in which decision rules for separating pattern classes are defined. This section introduces *Shape Analysis* (SA) which allows finding a symbol on topographic map presented in the form of the exterior outlines. An outline always leads to changes in intensity of an image. A major motivating factor behind the use of shape analysis is a collective understanding about symbol's form, size and orientation can be obtained from an external outline of the shape of symbol.

In the present work, canny edge detection technique is used and resulting edge segments with fixed length and slopes within different ranges are proposed as primitives for shape analysis in describing symbols on a topographic map. This method uses exterior outline to represent symbols. Complex valued chain coding encodes exterior outline and represents exterior spatial information. The illustration of complex numbered chain coding representation of outline is given in figure 1. Each vector of an outline is named as primitive vector (PV) and sequence of

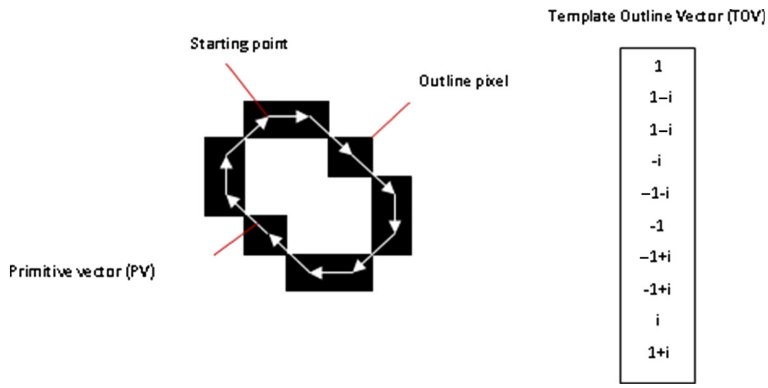



**Figure 1.** The illustration of complex numbered chain coding representation of outline.

complex-valued numbers are designated as template-outline-vector (TOV). The template outline vector does not depend on the orientation and counter change or interchange of the source image of the symbol. As the outline is encoded relative to starting point, this mode of coding is invariant with respect to the translation of an initial outline. Orientation of symbol on certain angle is equivalent to each PV of an outline on the same angle. The starting point modification conducts to TOV cycle shift. As PVs are encoded concerning the previous point, it is clear that as a modification of starting point, the sequence of a PV will be the same, but the first PV will be what begins at the starting point. The source image of symbol resizing can be considered as multiplication of each PV of an outline to scale factor. As a scalar product,

$$\eta = (\Gamma, \mathrm{N}) = \sum_{n=0}^{k-1} (\gamma_n, \upsilon_n), \tag{1}$$

where k is dimensionality of a TOV, $\gamma_n$ is $n^{th}$primitive vector of outlines $\Gamma$ of template, $\upsilon_n$ is n$^{th}$ primitive vector of outline N of test image. $(\gamma_n, \nu_n)$ is the scalar product of complex numbers. In shape analysis, primitive vector of identical dimensionality is considered for the scalar product. That is the number of the primitive vectors in outlines should be same.

### 4.1 *Normalized scalar product (NSP)*

In a proposed system, a measure of closeness of vectors is provided by $\eta$, normalized scalar product which is defined (Mehtre *et al.* 1997) as:

$$\eta = \frac{(\Gamma, \mathrm{N})}{|\Gamma|\,|\mathrm{N}|}. \tag{2}$$

The magnitude of $\Gamma$ and N i.e., length of outlines calculated as:

$$|\Gamma| = \left(\sum_{n=0}^{k-1} |\gamma_n|^2\right)^{\frac{1}{2}} \quad \text{and} \quad |N| = \left(\sum_{n=0}^{k-1} |\upsilon_n|^2\right)^{\frac{1}{2}}. \tag{3}$$

Here, elementary vector $\gamma$ and $\upsilon$ constitutes primitive vector as $\Gamma = (\gamma_0, \gamma_1, \ldots, \gamma_{k-1})$ and $N = (\upsilon_0, \upsilon_1, \ldots, \upsilon_{k-1})$, respectively.

The norm of the NSP has upper bound value as 1 if it is equal to product of arbitrary complex number and primitive vector of outline.

$$\Gamma = \mu \mathrm{N}. \tag{4}$$

The outline $\mu$N means it is the same outline N, but scaled to larger sizes. The size and orientation have been described by the arbitrary complex number $\mu$. The magnitude of the NSP reaches value one, if primitive vectors of two outlines are same, even though oriented at different angles and multiplied by some coefficient. The NSP concept is implemented in automated topographic map understanding system because topographic maps have a number of instances of the same object at various scales and orientation. For example, scalar multiplication of an outline mostly on them, but turned at a certain angle. The normalized scalar product of a vector on itself becomes 1. If outline turns 90 degrees, then it becomes 0+i, and if turn on 180 degrees gives −1. The properties of the NSP are shown in table 1.

Similarity measure is a function that computes the degree of similarity between two vectors. In the current study, the similarity measure has been implemented as normalized scalar product (Mehtre *et al*. 1997). The norm of the NSP is calculated using (7) to find maximum similarity between two outline vectors.

$$\left|NSP_{(\Gamma,\mathrm{N})}\right| = \left(\sum_{n=0}^{k-1} |\gamma_n|^2\right)^{\frac{1}{2}}. \tag{5}$$

Here,

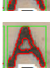
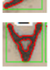
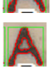
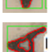
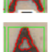
$$\gamma_n = \sum_{j=1}^{n} \left(f_j^q - f_j^i\right), \tag{6}$$

where, are discrete Fourier descriptor of query image and original image, respectively.

The NSP is extremely good for search of outlines similar among themselves. But there is one bottleneck problem not allowing it to use directly i.e., starting point selection for chain coding. The normalized value as per (6) is reached only if the starting point of outlines coincides. If outlines are identical but PV reference begins with other starting point then the norm of the NSP is not equal to a unity.

To overcome above limitation, interrelation function (IF) is implemented in this system. Values of this function show outline $\Gamma$ and N is how much similar if to shift starting point N on *m* positions. Interrelation function is defined on all set of PV but as cycle shift on k leads to an initial outline, with phase k. For an example, if N = ($n_1$, $n_2$, $n_3$, $n_4$), $\mathrm{N}^{(1)}$ = ($n_2$, $n_3$, $n_4$, $n_1$),

**Table 1.** Properties of the normalized scalar product of outlines.

| | | NSP | Real part of (NSP) = cos (a) | \|NSP\| |
|---|---|---|---|---|
|  |  | 1 | 1 | 1 |
|  |  | i | 0 | 1 |
|  |  | −1 | −1 | 1 |
|  |  | -i | 0 | 1 |

$N^{(2)} = (n_3, n_4, n_1, n_2)$ and so on. $N^4$ leads to N i.e., cycle shift on k leads to outline itself. Therefore, values of this function are considered only in limits from 0 to *k-1*. The magnitude having the maximum norm among values i.e., interrelations function (IF) value is calculated as:

$$\tau(m) = (\Gamma, N^{(m)}), \quad m = 0, ..., k-1, \tag{7}$$

where is the outline retrieved from the N by cycle shift on its PV by *m* elements.

Then similarity measure,

$$\tau_{\max} = \max\left(\frac{\tau(\mathrm{m})}{|\Gamma||\mathrm{N}|}\right). \tag{8}$$

The $\tau_{\max}$ gives a measure of similarity of two outlines invariant to transposition, scaling, rotation and starting point shift. The magnitude $\tau$ defines a degree of similarity of outlines, and becomes one of similar outlines, and argument $\arg(\tau_{\max})$ shows an angle of orientation of one outline, with reference to another. The list produced is ranked using $\tau_{\max}$ which is used in template matching.

### 4.2 *Estimation of shape descriptor*

The normalised scalar product (NSP) concept is implemented using shape descriptors and estimated as a Fourier descriptor for discovered outlines which are calculated by (6). The properties of NSP shown in table 1 have been implemented to make system's performance invariant to orientation of symbol or letter or number.

The last vector of an outline always leads to the starting point. Each vector of an outline has been named as a primitive vector (PV) and sequence of complex-valued numbers template-outline-vector (TOV). Outlines have been described by a vector $\Gamma$, in terms of their primary and basic vectors by $\gamma$ as $\Gamma = (\gamma_0, \gamma_1, ...., \gamma_{k-1})$. An operation over an outline of symbol yields a vector of complex valued code which has distinguished mathematical properties. Main motivation behind using a complex valued chain is that it is having resemblance with two-dimensional coding where the outline is specified as a population of the PVs presented in the two-dimensional coordinate reference model. If TOV is increased by some scale then the NSP will become 1 (simply to see from the (6)). The magnitude of NSP remains constant for various instances of symbols subjected to different instances at different transposition, rotation and scaling of outlines. The magnitude of the NSP of outlines becomes one in situation when these two outlines are coinciding. The NSP has been used to search the outlines and extract it from similar patterns. But it is susceptible to a starting point selection for chain coding. The matter is that the specified in (6) is true only if the starting point of outlines coincide. As the chain code has been used for template matching it must be invariant of the selection of starting point. Hence the difference in successive direction, i.e., interrelation has been implemented as an interrelation factor (IF)$\tau_{\max}$. It gives a measure of similarity of outlines after changing the starting point on template from one position to other position. Maximum of IF is invariant to transposition, scaling, rotation of objects and starting point shift on outline while encoding with the complex valued chain coding.

## 5. Methodology

Representation, description, classification and recognition are important tasks in any interpretation system. There are two critical steps in designing the map understanding system. First, to represent pattern images in flexible scheme and second is to perform matching on the representational scheme. There are many representation schemes used to describe the pattern image such as list, string, and the graph. In the present study, symbols are represented using a chain code technique which is a more flexible scheme for representation and description of pattern image also. After segmentation of symbols from the background, it is necessary to represent and describe its shape in characteristic features for computer processing during pattern recognition and understanding. Shape descriptor may be either internal or external descriptors depending on whether they encode the boundary of a shape or the part inside the boundary. In the present study, an external representation has been used which focuses on a symbol shape outline feature using the spatial organization of shape region, i.e., external space domain technique. One of the most common external space domain descriptor, boundary chain coding has been used to represent shapes. Most structural matching methods deal with graphical representations and string representations directly as in (Koo & Yoo 1998) whereas template matching has to be carried out using cross correlation and exhaustive search, i.e., translating the template over every position in the search area (Cox 1995). Template matching provides an effective way to interpret unknown samples by comparing them to a set of known prototype or template with same cluster index. Hence, template matching has been used to identify shapes. In template matching, the test image of the symbol has been matched with the stored prototype or reference pattern. Based on similarity criterion, the test image is interpreted as the prototype or template pattern that is the best match in the input. Top-down strategy has been used for recognition phase. It suggests a strategy in which system starts from the model of symbol and try to fit the model into the template database that is created in training. The flow graph illustrating the main phases in the development of the topographic map letter and number understanding system is shown in figure 2. The general sequence of an overall operation looks as:

(i) Pre-processing of the image such as smoothing, a noise filtration, contrast raise and enhancement.
(ii) Colour layer separation using k-means algorithm and deriving cluster value of each layer.
(iii) Binarization of the image and selection of outlines of symbols.
(iv) Filtration of the outlines.
(v) Conversion of outlines to uniform length i.e., outlines equalization. (If outlines of the same symbols are not of similar length then equalization is required. Inner product or cross correlation is possible for primitive vectors having uniform dimension.)
(vi) Search for all discovered outlines and searching of the template maximum similar to the given outline templates with same cluster value from binary model.

### 5.1 *Pre-processing*

The input for topographic map letter/number understanding system is a digital image of the Indian topographic map developed by the Survey of India. To extract data for the shape descriptor formation and matching stages, several steps of pre-processing are required. These include: smoothing, edge detection and generation of boundary chain. In our template matching algorithm, which is based on similarity of primitive $\tau$, the shape of the symbol, letter or number boundaries should be preserved during pre-processing. Artifacts due to badly generated templates would produce errors in the estimation of similarity measures and might result into incorrect recognition. To speed up the template matching process and reduce the number of false boundaries, the number of noise outlines generated in edge detection should be minimized. This is done by applying the smoothing operator to an input map. A canny edge detector is used to find edges in smoothing topomap. In most of the image analysis systems, binarization of the scanned gray level image is done prior to further processing. In the proposed method, locally adaptive binarization method is adopted for gray scale form of topographic map with low contrast and variable background intensity (Trier & Taxt 1995). Canny outlines are dilated for filtering. External boundaries are detected using a chain approximation algorithm. For descriptor estimation boundary data is converted into an ordered code using complex valued chain coding technique. Next, list of templates is obtained using shape analysis methods. For every object in topographic map input, colour separation phase returns value corresponding to a cluster. The cluster center obtained from k-means has been used later in the template matching. Also, the value of the cluster containing the objects obtained programmatically and k-means will not return the same cluster value every time. Here we calculated the cluster center value, which contains the mean 'a*' and 'b*' value for each cluster.

### 5.2 *The brief overview of implementation of functions for outline extraction, template generation*

In the present studies, outlines composed of pixel chains are extracted from a digital Indian topographic map via the canny edge detector (Roy *et al*. 2007) and used as an initial incomplete set of feature constraints. Smoothing a noise reduction technique has been applied for noise suppression in order to preserve the high spatial frequency detail (e.g., sharp edges) in digital topographic map. It has been explicitly implemented to remove noise in the form of isolated pixels of exceptionally low or high pixel intensity. A binarization method using local adaptive thresholding has been applied. The chain approximation method has been used to find outlines. Next, method to find template has been implemented. It also excludes templates inside other templates. The Outlines are created and stored using complex valued chain coding. A template name has been used as the recognized value. Template matching accelerates searching for a template for the given outline in each cluster by its colour/cluster index. Outcome of operation of this contains an initial outline, and the template discovered for the given outline in specified cluster. Besides, template description contains the degree of similarity, angle of orientation, scale of an outline and cluster index, relative to a template. Finally, templates with its description are stored as a templates model in binary file. When system receives the topographic map on an input, it outputs discovered outlines and recognized outlines.

### 5.3 *Representation and description process*

The outline of the symbol is a chain of points (pixels), separating it from a background. The boundary chain code describes the outline by a unit size segment with orientation. In the proposed system, the outline has been encoded by the sequence consisting of complex numbers. Then, the outline has been scanned in clockwise direction fixing a starting point on it and each vector of offset is noted by a complex number a+ib, where a - point offset on x axis, and b – point offset on the y axis. An offset has been preserved and noted concerning the previous point.

*Algorithm for outline extraction and complex valued chain code description*

Input: Digital Indian topographic map (figures 3a and 4a).

Output: Complex valued chain code of symbols.

(i) Apply k means segmentation method on enhanced topographic map image.
(ii) Derive cluster index and store it as a key for template matching.
(iii) Binarize image using local adaptive thresholding. (figures 3b and 4b)
(iv) Extract the boundary or outline of the symbol using the canny edge detector. (figures 3c and 4c).
(v) Remove noise by applying, erode and dilate morphological operations.

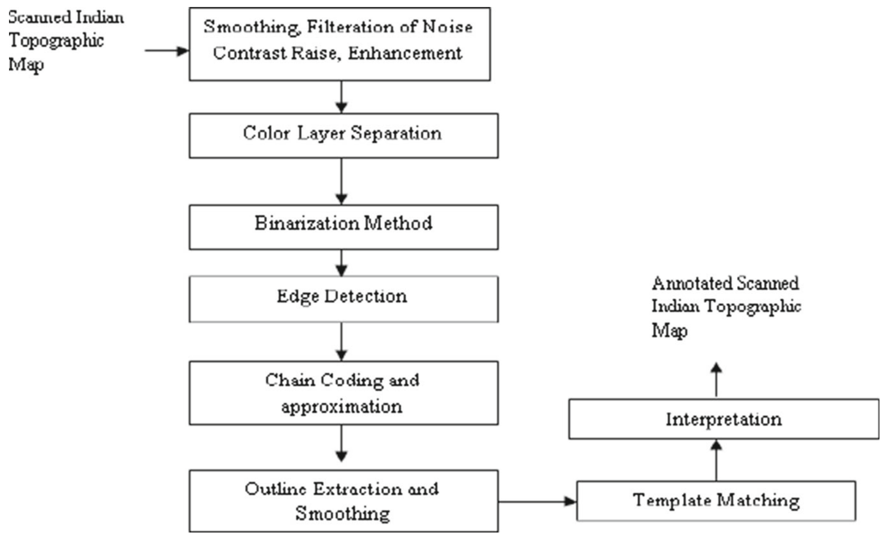



**Figure 2.** Flow graph illustrating the main phases in the development of the topographic map letter and number understanding system.

(vi) Trace the boundary in clockwise direction and generate 8 directional complex valued chain codes from 1 to 1+$i$.
(vii) Compute frequency of the codes.
(viii) Divide frequency of each code by the sum of the frequencies.
(ix) Combine the values in steps (vii) and (viii) to obtain feature vector of the template.

### 5.4 *Autocorrelation function*

In the present system, an autocorrelation function (AF) has been implemented and is always equal to IF (see (7)) for which N = Γ. It is a scalar product of an outline mostly on itself at various shifts of starting point i.e., $m$ defined as below:

$$\nu\,(m) = (\Gamma, \Gamma^{(m)}), m = 0, \ldots, k-1. \tag{9}$$

The AF does not depend on a choice of starting point of an outline. If the outline has any symmetry, then its AF has similar symmetry. The norm of an AF is symmetric concerning a central reference $k/2$ where $k$ is the dimension of TOV. As the AF is the total of pair wise product of a PV of an outline each pair meets two times at an interval from 0 to $k$. consider the graphics AF for some outlines as in the figures 3d and 4d. The norm the AF is represented by sky blue colour (if AF is represented only for an interval from 0 to $k/2$). An outline AF is implemented as characteristic descriptions of the shape of an outline. Template and corresponding auto-correlation function for some outlines is shown in figures 3e and 4d. From the boundary trace of shape a series of complex numbers are generated. If N samples of a closed Γ are taken, then it is defined by,

$$u(n) \triangleq x(n) + jy(n), n = 0, 1, \ldots, N-1. \tag{10}$$

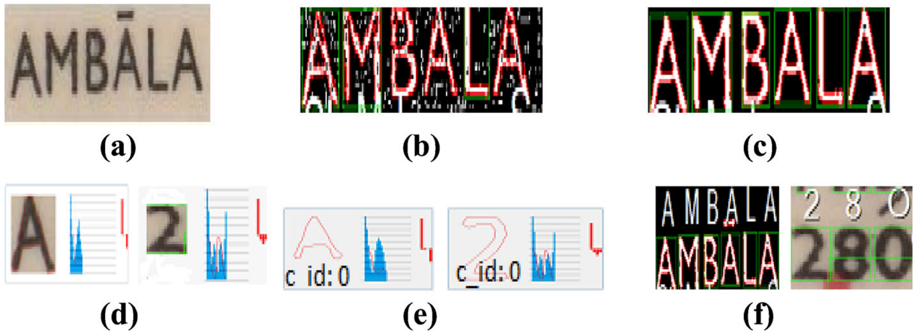



**Figure 3.** (**a**) A part of topographic map. (**b–c**) Outlines are filtered. (**d**) Outlines are equalized, in which AF descriptors are calculated. (**e**) Template matching is performed for the template which is maximum similar to discovered template pattern. (**f**) Letter and number are interpreted and understood by the system.

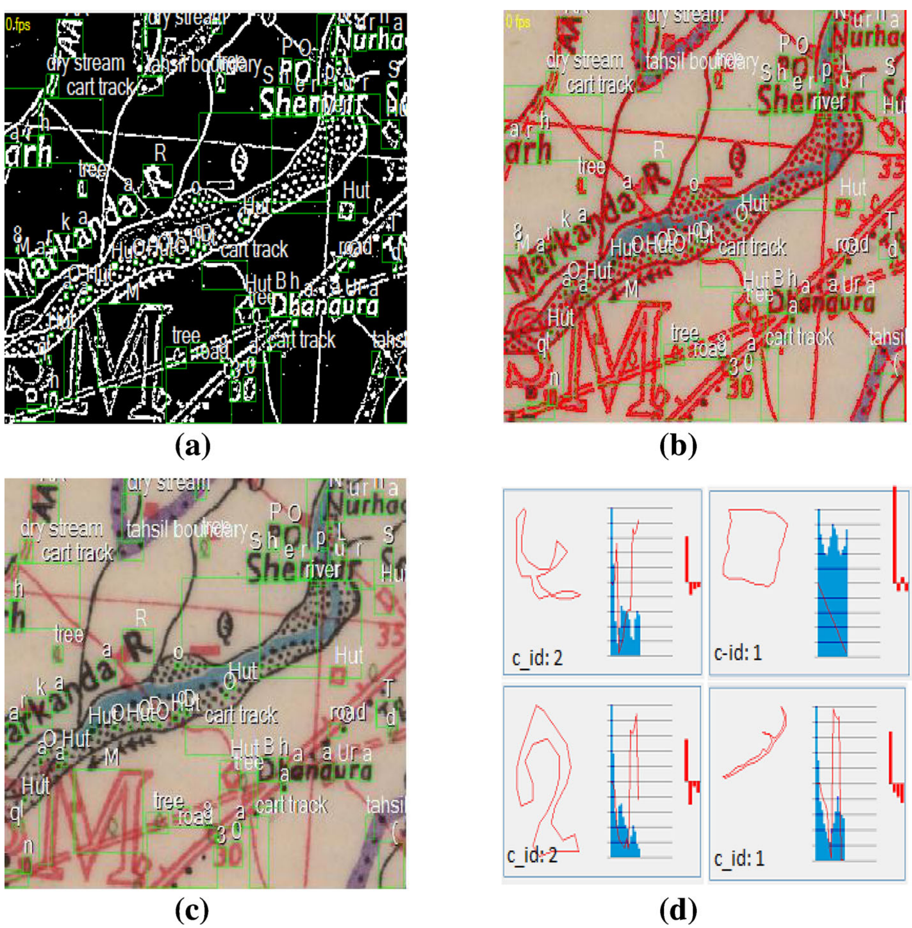



**Figure 4.** (**a**) A gray scale form of a topographic map, (**b**) Outlines are filtered. (**c**) Symbol are recognized and understood. (**d**) Outlines are equalized and AF descriptors are calculated which are used to find a template which matches with the template having same cluster index and most similar to the template pattern discovered.

Its discrete Fourier transform (DFT) is represented as follows

$$f(k) \triangleq \sum_{n=0}^{N-1} u(n) \exp\left(\frac{-j2\pi kn}{N}\right), 0 \leq k \leq N-1. \tag{11}$$

Discrete Fourier transforms which acts as a descriptor for a series of complex valued chain code has calculated using equation given above.

### 5.5 *Template matching*

After extracting the shape of symbol or letter or number, next is to match it against a set of template models with same cluster index. However, due to different orientation and interconnectedness within the topographic map, variation within the same type is not uncommon. The proposed study works on template matching, where the templates are formed by chain code. The templates and samples of symbols are digitized images. The degree of similarity between two digital images can be represented using measures of the match. In this approach, correlation measure is used to measure match. For digitized images which are encoded with Γ and N, the normalized cross correlation as a measure of a match is defined by the NSP and given by (2) and (3).

Then the Fast Fourier Transform (as given by (11)) has used to calculate the NSP.

The template matching algorithm implemented is as follows:

1. Separate colour layers of test toposheet and derive cluster index.
2. Generate template using algorithm for outline extraction and complex valued chain code description which is described previously.
3. Load the binary model containing all cluster value and set of templates.
4. Extract the shape of test symbol.
5. Derive cluster value.
6. Initialize the level of similarity of primitive to be 1.
7. Let representative ideal set having cluster value similar to that of test object.
8. Define the measure of match set.
9. If measure of match is not null return match. Otherwise search within representing ideal set having same cluster value.
10. If level of similarity is less than or equal to the maximum primitive level then step 4. In another case exit.

Toponym understanding in the Indian topographic map is illustrated using figure 3 which shows stages in letter and number understanding. Figure 3a shows a part of Indian topographic map. Figure 3b shows binarization of crop images by local adaptive threshold, and how the outlines are extracted by Image processing routines. Outlines are filtered that is shown in figure 3c. Figure 3d shows how outlines are equalized and AF descriptors are calculated. Figure 3e shows template, which matches with the template most similar to template pattern discovered. Letters and numbers are recognized and understood by proposed system that is shown in figure 3f. Symbol understanding in the Indian topographic map is illustrated using figure 4 which shows stages in symbol understanding. Figure 4a shows binarization of crop map image by local adaptive threshold, and how outlines are extracted by image processing routines outlines is filtered that is shown in figure 4b.

Symbols are recognized and understood that is shown in figure 4c. Figure 4d shows how outlines are equalized and AF descriptors are calculated and to find a match with the template most similar to the template pattern discovered.

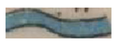
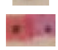
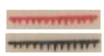
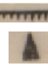
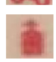
## 6. Experimental results

The system is trained with 150 samples of each of 20 types of symbols and 120 samples of characters and numbers forming toponym from National digital topographic database (NTDB) for OSM (Open Series Map) of Indian topographic maps. The developed system is tested for 200 samples of each type of symbol from NTDB. The small parts of a toposheet image of sizes 350X300, 800X600, 1500X400, and 2700X2900 scanned at 300dpi were taken for both training and testing. Let the image already binarized and on it outlines are selected. As further we will work only with points of outlines, we estimate their general amount on the image. For example, we take the maps of size n*n pixels. Then breed its uniform grid with a step s. The total length of all grid lines is: $L = 2n^2/s$ with this we are able to work with all pixels of images irrespective of, how many objects on it are represented. The complex valued chain code was computed for all the images in the training set by performing chain approximation algorithm described in section 5. Then, the recognition of the symbols was carried out using a template matching algorithm. In order to analyse how method will perform in practice, five-fold cross validation technique was used. The images were grouped into five-fold cross validation. Each iteration was carried out with one subset as a test set and the rest of the subsets have been combined to form training set. The result is shown in table 2. An overall recognition rate of 84.68% is achieved.

It is found that tree, antiquities, broken land and grass is having a higher recognition rate as compared to the rest due to their distinctive shape. The recognition error rate is higher for hut, road, river, river with rock, tank as we generated template for them are not always consistent and often intruded by other features resulting in variant templates at each instance. The chain approximation algorithm results in external spatial representation of symbols. The template generator creates template for each symbol and computes AF descriptor for the matching process. As an AF descriptor (represented by sky blue colour) values (see figure 4d) distributed and represented only for an interval from 0 to k/2, it is clear that if the exterior boundary has symmetry then its AF leads to symmetry.

Here, k is the dimension of template-outline-vector. The AF value of hut symmetrical and matches with many anti-pattern as well as template generated from small dot. So, the main power, tele-lines, dry wells on topographic map recognized incorrectly as hut or vice versa. Also, road, river, cart-track and many such objects whose shape cannot be defined by distinctive boundary always lead in incorrect recognizing. All these are the line features represented by irregular shape and size but distinct colour. Shape analysis is insufficient to define its peculiarity in shape. Also, template matching method gives results with maximum matches of AF. Thus, inductively trained system may misinterpret symbol ‘river with rock’ as a ‘river’. For such objects recognition rate is in between 80–90%. As training and testing images are taken from 300 dpi scanned topographic map, all symbols are not isolated, but suffered from overlapping with other symbols hence incorrect interpretation occurred. To evaluate the implementation, the symbol image dataset with two categories is segmented i.e., in the training set and a test set of images. The system is trained with the image from the training set. The learnt template patterns are stored in the binary model. The trained models are used to recognize symbols appeared in training as well as testing image with an overall success rate of 84.68%. The system described in this paper was trained and tested for two independent sets of 8 samples of each of 0 to 9

**Table 2.** Recognition rate for symbols in Indian topographic map.

| Symbols | Conventional symbols/legends | Five-fold cross validation | | | | | Overall recognition |
|---|---|---|---|---|---|---|---|
| | | Fold-1 | Fold-2 | Fold-3 | Fold-4 | Fold-5 | |
| Hut:Temporary;Permanent |  | 87.90 | 93.04 | 82.30 | 82.67 | 86.00 | 86.38 |
| Tree |  | 100.00 | 92.89 | 96.03 | 100.00 | 100.00 | 97.78 |
| Grass |  | 90.83 | 92.90 | 89.00 | 91.45 | 91.58 | 91.15 |
| Antiquities |  | 92.56 | 100.00 | 100.00 | 93.01 | 92.85 | 95.68 |
| Road |  | 86.90 | 92.90 | 90.54 | 82.00 | 91.78 | 88.82 |
| Dry stream |  | 90.76 | 90.70 | 89.87 | 91.98 | 87.99 | 90.26 |
| Cart-track |  | 89.87 | 90.77 | 91.45 | 92.78 | 89.02 | 90.77 |
| River |  | 90.67 | 88.43 | 91.32 | 90.70 | 87.90 | 89.80 |
| Broken-land |  | 92.30 | 90.54 | 92.89 | 96.03 | 100.00 | 94.35 |
| Well |  | 89.02 | 82.67 | 89.00 | 86.90 | 89.87 | 87.49 |
| Tahsil-boundary |  | 82.66 | 78.90 | 81.78 | 91.78 | 89.00 | 84.82 |
| Canal |  | 91.45 | 89.00 | 89.17 | 85.90 | 87.99 | 84.82 |
| Dams:Mesonary;earthwork |  | 87.90 | 86.34 | 92.90 | 90.54 | 88.00 | 89.13 |
| Tube well |  | 86.90 | 89.97 | 89.00 | 82.30 | 86.15 | 86.86 |
| Temple |  | 91.90 | 92.89 | 92.89 | 90.67 | 91.00 | 91.86 |
| Fort |  | 92.60 | 88.43 | 89.87 | 93.02 | 91.45 | 91.07 |
| Church |  | 88.90 | 87.00 | 92.30 | 91.11 | 88.92 | 89.64 |
| River with- rock |  | 72.67 | 80.05 | 78.45 | 75.00 | 76.01 | 76.43 |
| Tanks |  | 86.90 | 83.67 | 81.78 | 86.90 | 82.30 | 84.31 |
| Tower |  | 88.78 | 87.05 | 86.90 | 85.56 | 86.90 | 87.03 |
| Overall recognition | | 89.07 | 88.90 | 89.37 | 89.02 | 89.23 | 84.68 |

numbers with different orientation. Also, the system is trained and tested for 10 samples of each of capital and small A to Z letters in different orientations independently. The result of number recognition is shown in table 3. An overall recognition rate of 92.19% is achieved for numbers. The result of letters recognition is shown in table 4. The recognition rate of 91.73% is achieved for letters. It is found that 2, 3, 4, 5, 6 and 7 is having a higher recognition rate as compared to the rest due to their distinctive shape. The recognition error rate is higher for 0, 1, 8, and 9. The chain approximation algorithm results in external spatial representation of numbers. The template generator creates template for each number and computes AF descriptor for the matching process. The AF value of zero i.e., 0, 1, 8 is symmetrical and matches with other anti-pattern as well as template generated from letters also. So, the letter ‘o’, ‘O’, ‘i’, ‘I’ on topographic map recognized incorrectly as 0 and 1, respectively. Also, template of 8 and B matches with each other and results misinterpretation. The result of letter recognition is shown in table 4. Here, 10 samples are taken for each capital and small case but recognition result is not shown separately

**Table 3.** Recognition rates of numbers in Indian topographic map.

| Numbers | 5-fold cross validation | | | | | Overall recognition |
|---|---|---|---|---|---|---|
| | Fold-1 | Fold-2 | Fold-3 | Fold-4 | Fold-5 | |
| 0 | 90.00 | 88.00 | 87.19 | 82.77 | 82.10 | 86.01 |
| 1 | 80.00 | 82.25 | 82.10 | 90.00 | 88.60 | 84.59 |
| 2 | 92.92 | 98.03 | 97.64 | 98.03 | 98.41 | 97.00 |
| 3 | 98.82 | 98.03 | 95.28 | 99.61 | 98.41 | 98.03 |
| 4 | 98.03 | 97.64 | 97.64 | 98.82 | 96.83 | 97.79 |
| 5 | 87.19 | 82.10 | 90.00 | 82.25 | 88.00 | 98.03 |
| 6 | 96.07 | 97.64 | 95.28 | 98.82 | 95.63 | 96.69 |
| 7 | 99.61 | 97.64 | 98.43 | 98.43 | 94.44 | 97.71 |
| 8 | 82.25 | 82.10 | 82.77 | 88.19 | 79.21 | 82.90 |
| 9 | 82.19 | 85.00 | 79.61 | 82.43 | 86.43 | 83.12 |
| Overall recognition | 90.71 | 90.84 | 90.59 | 91.94 | 90.81 | 92.19 |

**Table 4.** Recognition rates of letters in Indian topographic map.

| | Correctly recognized (20 samples) | Incorrect recognition | | Overall recognition (%) |
|---|---|---|---|---|
| | | Not recognized | Wrongly recognized | |
| A/a | 20 | 0 | 0 | 100 |
| B/b | 17 | 1 | 2 | 85 |
| C/c | 19 | 0 | 1 | 95 |
| D/d | 17 | 0 | 3 | 85 |
| E/e | 19 | 0 | 1 | 95 |
| F/f | 20 | 0 | 0 | 100 |
| G/g | 18 | 0 | 2 | 90 |
| H/h | 20 | 0 | 0 | 100 |
| I/i | 17 | 1 | 2 | 85 |
| J/j | 18 | 0 | 1 | 90 |
| K/k | 17 | 1 | 2 | 85 |
| L/l | 19 | 0 | 1 | 95 |
| M/m | 19 | 0 | 1 | 95 |
| N/n | 19 | 0 | 1 | 95 |
| O/o | 17 | 0 | 3 | 85 |
| P/p | 18 | 0 | 2 | 90 |
| Q/q | 17 | 1 | 2 | 90 |
| R/r | 17 | 1 | 2 | 90 |
| S/s | 19 | 0 | 1 | 95 |
| T/t | 18 | 1 | 1 | 90 |
| U/u | 20 | 0 | 0 | 100 |
| V/v | 18 | 1 | 1 | 90 |
| W/w | 20 | 0 | 0 | 100 |
| X/x | 19 | 0 | 1 | 95 |
| Y/y | 17 | 1 | 2 | 85 |
| Z/z | 18 | 1 | 1 | 90 |
| Overall recognition | 477 | 9 | 33 | 91.73 |

for capital and small case. Letters A, F, H, U, and W show highest recognition rate whereas letters B, D, I, K, O, and Y are recognized wrongly with small recognition rate. Many such letters or numbers, whose shape cannot be defined by mere exterior boundary, always lead to incorrect recognizing. Shape analysis using the exterior spatial descriptor is insufficient to define its peculiarity in shape. Also, template matching method gives results with maximum matches of AF. Hence, even though the system is inductively trained for zero gives it as letter 'O'. The letters and numbers touching with other symbols or letters and numbers always yield misinterpretation.

Hence to improve recognition rate, optimal segmentation method need to be researched further. Important achievement is that computational complexity is low. Comparing an AF, generally, does not save us of the necessity of an evaluation an IF. Only the IF states an exact estimation of closeness (i.e., similarity) of outlines. The AF, generally, can coincide for various outlines. But, thus, preliminary selection of templates on an AF essentially narrows down count of candidates on comparing on an IF.

### 6.1 *Evaluation metrics*

An important criterion for testing the efficiency of the search and retrieval is that the output must include all the similar images (Alvarez 2002).

The list produced is ranked using$\tau_{\max}$. Hence, to evaluate the performance of retrieval, the merit the efficiency of retrieval, $\eta_T$ is used. $\eta_T = \frac{w}{n_1}$, if $n_1 \leq n2$; and $\eta_T = \frac{w}{n_2}$, if $n_1 > n2$; where, $w$ is relevant symbol/letter/number which is recognized. Here, $n_1$is $w + x$ and $n_2$ is$w + y$.

Variable $x$ is defined as relevant symbol/letter/number but not recognized and $y$ is defined as non-relevant symbol/letter/number but still recognized.

Recall- All the symbol/letter/number recognized by the system, out of the topographic map symbol that is relevant, is called as Recall. Recall is calculated for training (TR) and testing (TS) samples separately as:

Symbol: Recall (TR) = $\frac{w}{n_1} = 0.9724$ and Recall (TS) = $\frac{w}{n_1} = 0.944$

Toponym: Recall (TR) = $\frac{w}{n_1} = 0.8407$ and Recall (TS) = $\frac{w}{n_1} = 0.80$

Precision– All the symbol/letter/number from topographic map that are recognized by the system, but how many are relevant gives a precision value. Precision is calculated for training (TR) and testing (TS) samples as:

Symbols: Precision (TR) = $\frac{w}{n2} = 0.9745$ and Precision (TS) = $\frac{w}{n2} = 0.8832$

Toponym: Precision (TR) = $\frac{w}{n2} = 0.7971$ and Precision (TS) = $\frac{w}{n2} = 0.7255$

Standard evaluation metrics start with a contingency table (Alvarez 2002). Tables 5 and 6 describe evaluation metrics and the accuracy of the proposed system for symbols and toponym, respectively. The feasibility of the topographic map symbol understanding system has been evaluated for training and testing sample separately. The trained models are used to recognize toponym appeared in training as well as testing image. Outcome of tests is compared, resulting in precision = 0.7971, recall = 0.8407 for training samples (TR) and precision = 0.7255, recall = 0.80 for testing samples (TS).

Symbols: Accuracy (TR) = $\frac{w}{N} = 0.9125$, and Accuracy (TS) = $\frac{w}{N} = 0.9262$.

Toponym: Accuracy (TR) = $\frac{w}{N} = 0.9135$, and Accuracy (TS) = $\frac{w}{N} = 0.9629$.

**Table 5.** Contingency table for accuracy assessment of symbol understanding.

| Symbols | | Training (TR) | Testing (TS) | Overall accuracy $w/(w+z)$ |
|---|---|---|---|---|
| Relevant/correct | Recognized ($w$) | 2608 | 2360 | (Overall $w$:4968 |
| | Not recognized (x) | 74 | 140 | Overall z: 438) |
| Not relevant/incorrect | Recognized (y) | 68 | 312 | 91.89% |
| | Not recognized (z) | 250 | 188 | |
| Recall | $w/(w+x)$ | 0.9724 | 0.944 | |
| Precision | $w/(w+y)$ | 0.9745 | 0.8832 | |
| Accuracy | $w/(w+z)$ | 0.9125 | 0.9262 | |

**Table 6.** Contingency table for accuracy assessment for toponym understanding.

| Toponyms | | Training (TR) 260 samples | Testing (TS) 260 samples | Overall accuracy w/(w+z) |
|---|---|---|---|---|
| Relevant/correct | Recognized ($w$) | 169 | 156 | (Overall $w$:325 Overall z: 22) |
| | Not Recognized (x) | 32 | 39 | |
| Not relevant/ incorrect | Recognized (y) | 43 | 59 | 93.65% |
| | Not Recognized (z) | 16 | 6 | |
| Recall | $w/(w+x)$ | 0.8407 | 0.80 | |
| Precision | $w/(w+y)$ | 0.7971 | 0.7255 | |
| Accuracy | $w/(w+z)$ | 0.9135 | 0.9629 | |

Here, $N$ is equal to $w+z$. Variable $z$ is defined as non-relevant symbol/letter/number which is not recognized. Overall percentage of accuracy for symbol is 91.89%. It is calculated as: (4968/5406)*100 = 91.89%.

The overall percentage of accuracy for toponym retrieval is 93.65%. It is calculated as: (325/347) * 100 = 93.65%.

## 7. Conclusion

Topographic maps provide valuable information to a planner or surveyors, but their understanding remains a time-consuming and subjective task. Extraction of information from Topographic map through digitization or vectorization requires human–computer interaction. However, the resulting product is not intelligent enough to handle automated map analysis. The shape analysis method reported in this research work provides a new representation and a description paradigm. Structural approach applied to pre-processed map provides a flexible scheme to represent and describe shapes of boundary outlines using complex valued chain coding. The shape encoding has been constructed to consider orientation and starting point selection criteria. Also, interrelation function and autocorrelation function are implemented for searching outlines similar among themselves and to overcome difficulties with the normalized scalar product. Template matching has been implemented based on similarity measure which is having less computational complexity. If the base of $t$ number of templates store their AF, searching of a template for a outline of length $k$, by comparing the AF, makes $O(k^2t)$ which is good estimation. Testing method of system yields 84.68% recognition rate of the symbols of an Indian topographic map. Also, accuracy of retrieval is 91.89%. The recognition rates of letters and numbers are 91.73 and 92.19%, respectively. The overall percentage of accuracy for toponym retrieval is calculated as 93.65%. While the performance of the Indian topographic map understanding system described here is promising, the fully automatic understanding of digital raster maps remains an open problem due to the complexity, wide variability of the characteristics and heavy interconnectedness of different features of topographic maps. The future scope of the study will be to address the specified problems as well as better segmentation and recognition scheme to develop learning and reasoning capacity in the system. It will provide comprehensive solution to understand complete topographic map irrespective of the complexity and wide variation.

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