Medical Image Segmentation

A Dissertation

Submitted in partial fulfillment of

the requirements for the award of the degree

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MASTER OF TECHNOLOGY

in

ELECTRONICS AND COMMUNICATION ENGINEERING

(With Specialization in Communication Systems)

By

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CANDIDATE'S DECLARATION

I hereby declare that the work carried out in this report entitled Medical Image Segmentation using Fuzzy C-means Clustering is presented on behalf of partial fulfillment of the requirement for the award of the degree of Master of Technology with specialization in Communication Systems, submitted to the Department of Electronics and Communication, Indian Institute of Technology, Roorkee, India, under the supervision and guidance of Dr.Vinod Pankajakshan, Assistant Professor, ECE, IIT Roorkee. The content of this dissertation have not been presented by me for the grant of any other degree of this or any other institute.

DATE : .... SIGNATURE:

PLACE: Roorkee (Rakesh Kumar)

CERTIFICATE

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

DATE : .... SIGNATURE:

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Rakesh kumar

Abbreviations

FCM	Fuzzy C Means
KM	K-means
ANN	Artificial Neural Network
DN	Deep Network
KNN	K-Nearest Neighbours
SDAE	Stacked Denoising Auto Encoder
CT	Computed Tomography
MRI	Magnetic Resonance Imaging

ABSTRACT

Bio-medical image segmentation is one of the most important studies in the field of medicine, as well as the results obtained by the diagnostic guide for diagnosis, treatment planning and verification of managed treatments. Therefore, accuracy is as important in analysis of bio-medical images as we have accuracy in data acquisition systems.
Medical image segmentation helps in the research of brain tumor prediction, biopsy, guidance, prognosis monitoring, disease stage identifi

cation, therapy planning, and therapy response. The Tumor is the accumulation of abnormal cells. [1] Brain tumor is the most common cancer in infants and adolescent. In the case of Glioma, It is the most common form of the malignant tumor. which are heterogeneous in nature. starting the diagnosis earlier will help them to extend their valuable life. Nowadays fully automatic methods have been able to achieve state-of-art results using computed tomography images NS Magnetic Resonance Image which could give better tissue images. Bio-medical imaging system requires the consecutive application of different kinds of imaging techniques to be used to quantify and analyze the predicted characteristics. The main purpose of this dissertation is to model algorithm that enables the analysis and quantification of various functions in medical imaging with minimal input dependence on results.
As part of this dissertation study, a comprehensive literature review is conducted and a new groundwork for analysis and processing of medical images is implemented, including factors subjected to the automation of individual processes

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Chapter 1

Introduction

1.1 Motivation

Medical image processing and scrutiny has vast importance in the field of medication, specially in non-invasive operation and radiological study. [2] There is huge dilemma in medical image scrutiny and analysis involves the urgency for a computer system that understands images and image framework and knows what that means. Correct interpretation and scrutiny of medical images generally becomes tedious and time-consuming, because there are many details in these images. Recent advancements in bio-medical imaging and processing of medical imaging have significantly reduced the requirements for surgical mediation in the treatment of different kinds of diseases.

Medical images needs the consecutive application of many techniques for subsequent image processing, like enhancement, organization, fragmentation, or recording, for use in the quantification and analysis of expected characteristics. These characteristics can be explicit component of the image, such as specific tumors or lesions, as well as any analytical property throughout the biomedical image.

With times, several innovations have been developed to allow manual, semi-automatic or fully automated medical image data processing by engineers and non-engineers. However, the efficient usage of several of these algorithms areas needs a significant extent of human cooperation. This type of attitude generates many refusals, like the hardship of usage and the divergence of consequence gained.

Within the scope of this dissertation, a new groundwork for bio-medical image processing and analysis has been developed based on a comprehensive review of recent literature on image processing.

1.2 Objective

The main objective of this dissertation is to study the different image enhancement techniques and medical image segmentation techniques and compare the results of different medical image segmentation techniques by using some parameters and finding out best technique for brain tumor segmentation.

1.3 Brain Tumor

Brain tumor is the second most common cancer in children. There exist 130 different kinds of tumors. With age, rate of brain tumor increases. [3] But compared to other kinds of cancer, they are relatively frequent in all age groups. A tumor is a mass of tissue that is formed by the accumulation of abnormal cells. [4] Brain tumors are of two types. One is those which are inside the brain substance and another one are those which are outside the brain push the brain. [5] The most common is glioma in which the tumor occurs within the brain. Metastatic tumors are tumors that come from another part of the body or organ and present in the brain. The pituitary gland begins in the pituitary gland and these tumors can affect pituitary hormones throughout the body. Primitive neuroticodermal tumors are rare embryonic cancer cells in the brain that can appear anywhere in the brain. Tumors that suppress the brain outside the brain are called meningiomas. They fall under the general classification of a brain tumor. The symptoms arising from these tumors vary. [6] Treatments vary depending on the tumor seen in the scan report. These images lack the location, size, symmetry of tumor size and also differentiate the types of cells that are edema, necrotic, non-potent and enhancer that combine to form the entire tumor, in the tumor and all. Tumors improve. A brain tumor is diagnosed by a neurological examination using imaging modalities such as CT (computed tomography), positron emission tomography (PET), magnetic resonance imaging, angiogram, biopsy, and span puncture. After obtaining the results of these imaging modalities, they can find different degrees of tumor. It really only tells what the growth potential is and the type of tumor biology. It determines what treatment will be for that person. For a low-grade glioma patient, the first observation is the diagnosis of radiation and chemotherapy for the high-grade glioma patient. For metastatic tumors, treatment includes surgery followed by focused radiation. Includes observation of patients

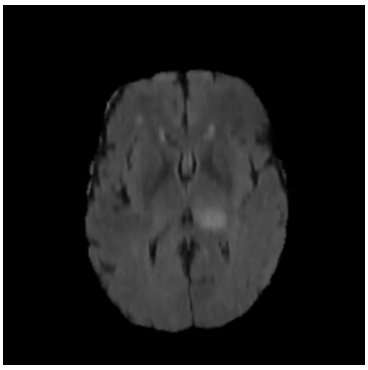

Fig. 1.1. FLAIR

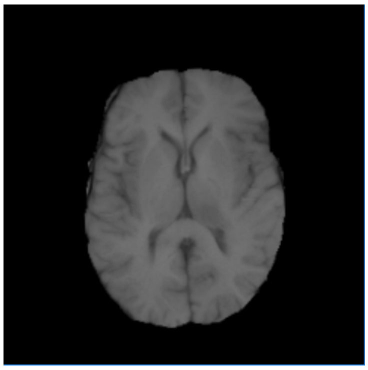

Fig. 1.2. T1

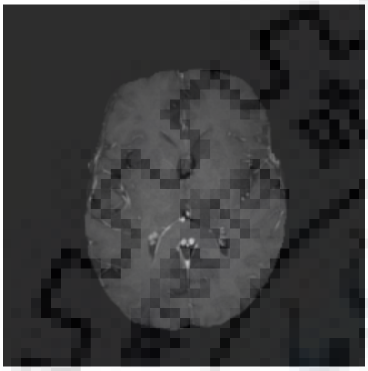

Fig. 1.3. T1-ce

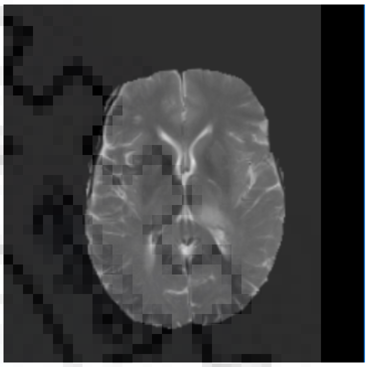

Fig. 1.4. T2

with meningioma after surgery. [7] Magnetic resonance imaging has been shown to provide quality data or information about tumors, specifically gliomas. MRI provides quality data or information about tumors, specifically glial cell gliomas. MRI images of four different types are used to capture contrast images. There are four models used in this model, the fluid downgrade investment recovery, native T1, weighted on T2 (T2), weighted on T1 (T1Gd). Each of the four modalities corresponding to the particular patient provides a total of 155 D images to represent the three-dimensional shape of the brain. Two-dimensional image segmentation is a 240 x 240 image, therefore, each model produces a total of 155 x 240 x 240 images for a patient.

1.4 Problem statement

Here, method for brain tumor segmentation named k-means clustering and Fuzzy C-means clustering will be presented.

1. The primary aim of this research is to develop an algorithm which should be able to take a magnetic resonance image as an input and should give better classification than other algorithms.

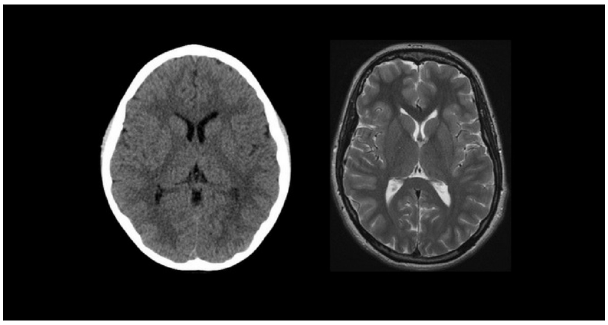

Fig. 1.5. CT image vs MRI image

2. Wiener filter,median filter and anisotropic diffusion filter will be used for noise removing.

3. Designed and developed a valuable computer-aided diagnosis system for brain tumor segmentation using clustering algorithms.

4. The continuation of the earlier project, coding develop the accuracy and improve the speed of the classification and segmentation.

1.5 Main Contributions

A detailed review of the literature on image processing is done, and the in-depth investigation of image processing routines and the mathematical relationship between them is done. Our review directs the reader to previous work related to each topic and presents a detailed mathematical background behind numerical solutions for the implementation of problems and chosen methods.

A prototype tool is built using data structures developed within the scope of the application framework. The first 2 modules of the application framework are presented here, each with multiple functions and capabilities. These modules are:

Image restoration part,and

Image Segmentation part

Detailed information on implementation, validation and experiments carried out with these modules is presented in the respective chapters. The image enhancement module allows the application of some image restoration and regularization techniques. The image size, Wiener filter, medium filter, Gaussian filter and contrast enhancements are implemented at this point and attached to the module.

In the image segmentation module, we describe generalized spatial diffusion c-means algorithms for medical imaging the division.

Chapter 2

Image Enhancement Techniques

Image enhancement technique is like an image process Processing so that the result is more adequate than Original image for a specific application. Of this improvement The stored digital image is created with the help of MATLAB Software [7]. The proposed approach is shown in Figure-1

The proposed steps in the preprocessing technique are (Simultaneous, noise elimination, filtering and vice versa improvement) 1. Real-time magnetic resonance image is obtained from Gemini Scanning center 2. The color image becomes a grayscale image.
3. Images are sized to different sizes.
4. Gray image is finished using noise Many filtering techniques. 5. Image contrast is enhanced by applying Adaptive histogram equalization for filtering Technique.
6. The received image is the enhanced output image.

2.1 Image resizes

Image resizing is an important role in the image. Processing technique to enhance and reduce the given image Pixel format size. Image interpolation can be divided into There are two different methods, they are image sampling and ascending sampling. Which is required to resize the data Coincide with the specific communication channel or Exit Screen. While it is more efficient for low transmission An estimate of the resolution version for the client An original high resolution may be required to present the final version. A precise sizing of visual data image data is required. Steps from multiple consumers to multiple applications Products for important functions within medicine, security and

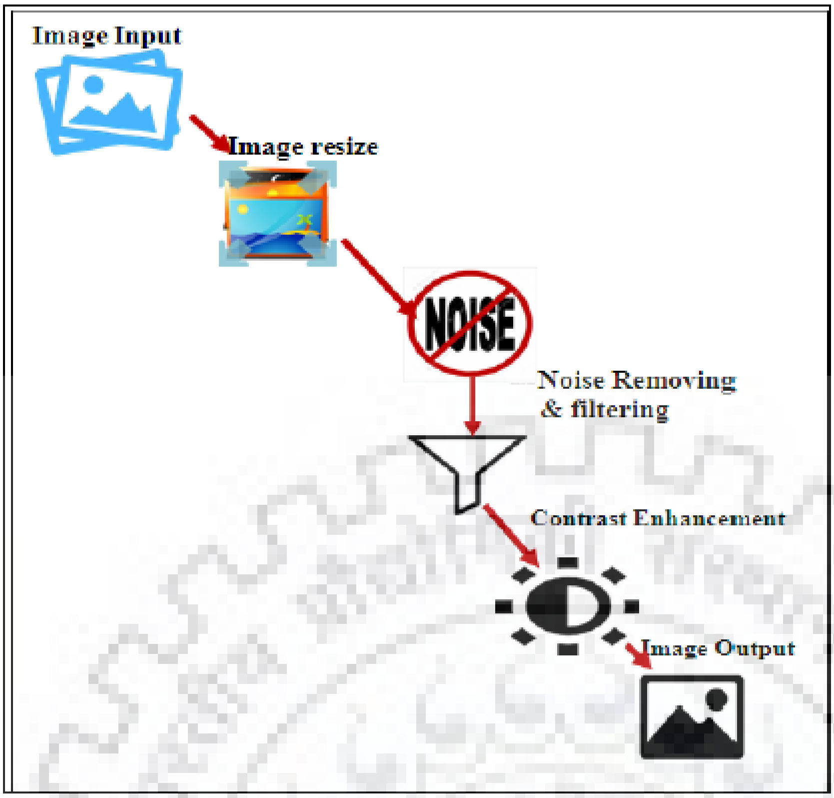

Fig. 2.1. Preprocessing Methodology.

Defense sector was the nearest neighbor algorithm technique Implemented in this section as part of image resizing Technique. Nearest neighbor implementation The technology makes the final process much faster for processing Image.

2.2 Filtering Methods

Filters have a filtering technique to improve the image It is mainly used to suppress high frequencies Image, ie, soften the image, or lower frequencies, Correcting or detecting edges in an image. for example You can filter an image to emphasize or remove certain features Other Features Many technologies are available and The best option may depend on the image and how it will be used. Image filtering is useful for many applications including Smoothing, fast, noise elimination and edge detection.

2.2.1 Wiener

Wiener filtering makes optimal compensation Between reverse filtering and noise smoothing. Remove Reversible additive noise and simultaneous blur. This type of filter is excellent in a sense that its mean squared error is very less. That means, wiener filter reduces the almost all mean squared error. In inverse filter there is no provisioning for noise reduction bur in wiener filter noise reduction is considered. Wiener filter is a linear process. Wiener filtering work on the basis of statistical process. In Fourier domain the equation for it is expressed as follows:

$$G(x, y) = \frac{H * (u_1, u_2) F_{xx}(u_1, u_2)}{H(u_1, u_2) 2 F_{xx}(u_1, u_2) + F_{nn}(u_1, u_2)} \tag{2.1}$$

2.2.2 Median

The average filter operates in a rectangular region. this Sit filtering operation on the pictures In some of the conditions listed below. among output The elements have an average value of about 3 to 3 According to the input elements in the pictures. no However, to change the edges of the images. production 'What is his peculiar feature, that replaces the current filter pixel. And (x, y), where S is the center point of this is that time. These marks is used.

P_{min}= minimum pixel value of image

P_{max}= maximum pixel value of image

P_{med}= median pixel value of image

Medium filtering is used to soften impulsive noise i.e. if there is abrupt changes in intensity then that can be removed with the help of median filter. In a median filter, a mask of size 3*3 or 5*5 slides along the image, and the median intensity value of the pixels within the mask becomes the output intensity of the pixel being processed in that image. For example, suppose the pixel values within a window are 1,2,4, 53, 11,19, and 23 suppose the pixel whose value we have to calculate is 4.Then the value of median filter for that pixel position is 11, which is the median of above seven pixels. Median filtering polishen the image as lowpass filter smoothes and is thus useful in noise reduction. But contrary to lowpass filter, median filter preserve dissimilarity in a step function and make uniform only some of pixels which has pixel values very large compare to surroundings pixels. And it does not affect oter surrounding pixels. Mask size is the critical criterion for median filtering.Choosing perfect mask size for filtering is very difficult task.It is choosing by experimenting different mask size and then choose best one which gives best result.

2.2.3 Anisotropic

In magnetic resonance images anisotropic filtering has been used for a very-long time of period. And it produces very good results. [8]

It is a non-linear diffusion process, which make diffusion in a uniform manner but stop diffusion at large variation of intensity i.e. at edges.

Anisotropic diffusion filtering is also called Perona-malik diffusion filter. [9] Noise is removed by diffusion process by taking use of heat equation that is partial differential equation.But heat equation do diffusion in an isotropic manner which is equivalent to images filtering with gaussian filter. [10] Perona-malik filter take use of edge stopping function, which makes it non-uniform filtering.

2.3 Contrast Enhancement

The difference between the maximum and the minimum pixel is known as contrast. This formula to extend the histogram or increasing the contrast is given below:

$$f(x,y) = \frac{s(x,y) - s_{min}}{s_{max} - s_{min}} * 2^p \tag{2.2}$$

The formula needs to find the minimum and maximum pixels multiplied by the degree of intensity of gray color. In my case, the image is 8p, so there are 256 levels of gray. The minimum value is 0 and the maximum value is 230. So the formula in my case is

$$f(x,y) = \frac{s(x,y) - 0}{230 - 0} * 255 \tag{2.3}$$

where s(x,y) represents the value of every pixel intensity.

2.4 Types of Noises present in medical images

Gaussian noise

There was a noise around and within the channels.Since communication probability density function Gaussian noise is equivalent to that of the normal distribution. Therefore, when it is called Gaussian distribution. Scattered evenly Gaussian noise signal. Pixels can be summarized as the pixel value of the noisy image of the total amount of matter and arbitrary Gaussian noise had dispersed.

Salt and Pepper Noise

This is known as impulse noise and tumult, and salt and pepper, the noise of the spike. That is, if the lighting elements in the dark and bright country in the dark region of the pixel image in the image. Values can be obtained salt value and pepper noise is high and low value. Basically, it is born of ignorance due to the conversion of analog and digital communication, due to bit errors. It is particularly important that the original image refers to the depravity of their knowledge of keeping a beast, salt and pepper out of the noise.

Speckle Noise

The mottling noise deteriorates the image of the flag and, in particular, the recognition or the same as the plan was placed at the time of requesting details about the ultrasound images. It is a type of which the sound is multiple. Granular noise can be defined with reference to granulated noise and deteriorates the quality of medical ultrasound images. A Speckle noise follows a gamma distribution.

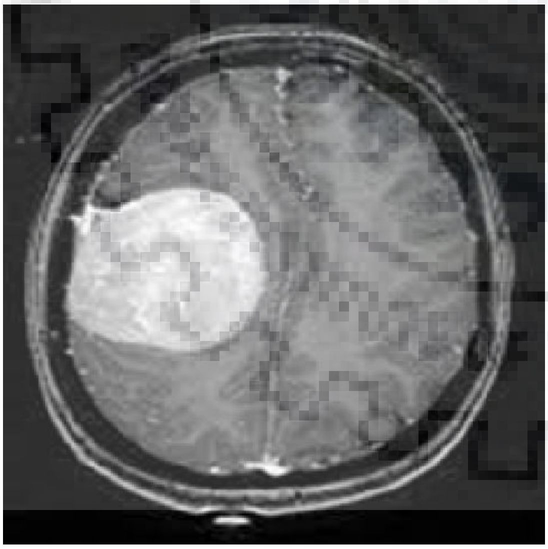

Fig. 2.2. Before anisotroping filtering

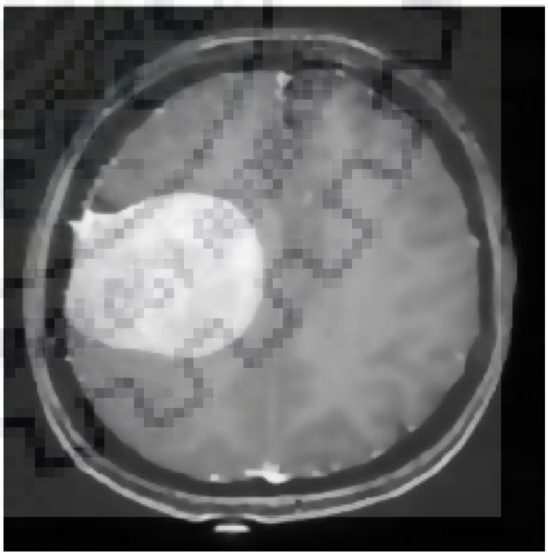

Fig. 2.3. After anisotroping filtering

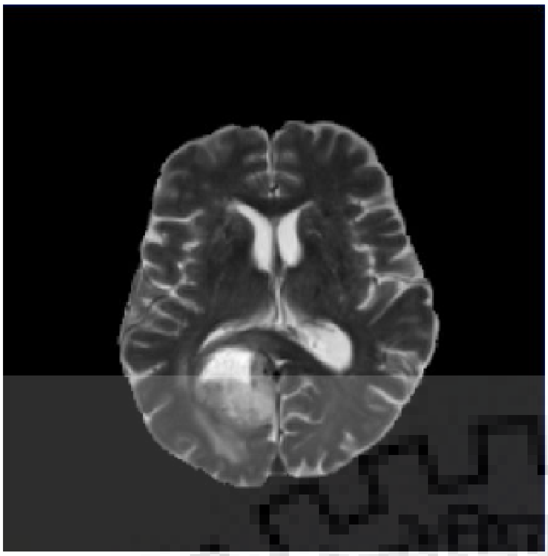

Fig. 2.4. Before filtering

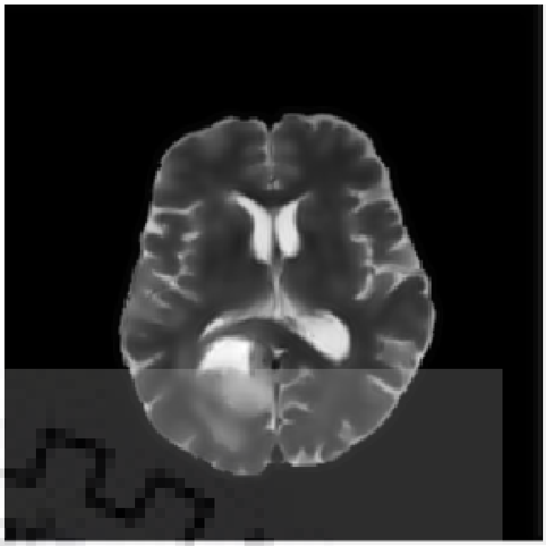

Fig. 2.5. Wiener Filtered Image

2.5 Methods for Segmentation

Brain tumor segmentation methods can classified as manual segmentation, semi automatic segmentation and fully automatic segmentation.

2.5.1 Manual segmentation

The Greek medical radiologist segment only from the normal way of practicing the anatomy of the tissue and damaged tissue. It is a slow and difficult task. It must pass through the pixel one by one, each of the SAMK segments. HGG patients suffering from them is much less survival time is fast and without the need for manpower to human errors. The slices are articulated manually, such as the image of the magnetic resonance images of the earth.

2.5.2 Semi Automatic segmentation method

In semi forms that the time interval is not the easiest of an initialization of the rebates algorithm. In his own feedback on the algorithm for feeding the weights behind him, and at the end, at the time of the event. During the initialization stage first draw a base around which the tumor has been divided into segments each, then run through the user algorithm rebates you can direct the best results by adjusting the parameters. [] This process is faster than the manual method of therapy, but they also depend on the user. Therefore, there was a need to go from just to fully automatic.

2.5.3 Automatic segmentation method

This class is determined by the model that is developing a magnetic resonance image of the model results in many different regions and started to lebelled image representing the tumor. Next, the connection between the image and waiting to establish the truth on the ground began. Before the main manufacturing stages such as feature extraction, and after lion therapy. Pre-processing to eliminate noise and the level of training would be changed to carry out all patients. The representatives of the ie, after the MRI image, these characteristics are given by casting the outer layer, which is directly applicable to each type of fabric. Various image processing methods are those that participate in extract functions. Now, as can be seen from these classifying features, such as support vector machines, etc. Neuronal Network the righteous, the results have to be given birth. One of the main problems with the traditional modes of division, which is the selection of features and that they represent, and were given in. In this way, the new trend is the fact that he has the image of a profound doctrine based on algorithms and the characteristic of using, in general, the doctrine of raw data that he had with him. Therefore God is not at all, he conducts the process of the work to be openly to the drawing of a pen. In recent times many ways to be able to reach the fully automatic state of the art results.

2.6 Techniques for segmentation

Various segmentation techniques used for brain tumor segmentation notable advantages and limitation discussed below.

Thresholding method

This method separates the region by comparing different intensity levels. Threshold method take use of histogram for contrasting different intensity regions.

Region growing technique

In this method, first of all seed location is selected and homogeneity criterion is choosen.Then nearby pixels are checked by this criteria and the pixels which satisfy the given critria are included in that region.Thus region grows by connected and similar pixels. [11]

segmentation by neural network

Here, samples of image data are trained in a neural network and then this trained data is used to segment other images.Fuzzy logic is also used with neural network to segment the image.It is equivalent to conventional pattern recognition.

Edge based technique

Edge based method take use of changes of grey tones in an image. Edge based technique gives better results for images which has larger contrast between difeerent objects in an image. if the image has too many edges this method is not suitable.

Clustering method

Clustering Method divides uniform pixel values into same group. Each group is called cluster.There are two types of clustering that is k-means clustering and fuzzy c-means clustering.

Chapter 3

PROPOSED IMAGE SEGMENTATION METHODS

3.1 INTRODUCTION

IMAGE SEGMENTATION is partition of an image into multiple meaningful (easier to examine) partitions or segments. Bio-medical image segmentation partitions the pixels in different regions like glioma and brain tumor. The Pixels in each segments share common property (ex: pixel intensity). It gives a correct diagnosis by evaluating brain tumor and glioma. Therefore, medical image segmentation is presently becomes imperative indicative image segmentation technic for initial revelation of anomalous variation in cells and organs. Large number of image analysis and processing technics has developed for magnetic resonance imaging segmenta-tion which are as follow: thresholding, region growing, and clustering.Since medical images have limited spatial resolution, poor contrast, noise, and non-uniform intensity variation,pixel based segmentation techniques leads to inaccuracy.Fuzzy clustering techniques such as fuzzy C-means clustering algorithm is more robust methods for medical image segmentation.So, Fuzzy clustering is pertinent method in medical image segmentation.In this dissertation, image segmentation is done by two algorithm that is k-means clustering algorithm and fuzzy c-means clustering algorithm. Also, spatial fuzzy c-means clustering is studied in which both fuzzy values and spatial values are considered for segmentation.Fuzzy c-means clustering was developed by James Bezdek in 1980s.After that large number of clustering approch has developed to give robust segmentation results.A lot of research work have been carried out to improve the clustering algorithm.

FCM clustering algorithm performance is evaluated by modifying the membership value. FCM clustering is also called soft clustering method because pixel have membership in all classes of clusters. FCM has drawback of computational complexity and if noise is increased then its performance is reduced.

3.2 Image segmentation with k-means clustering algorithm

k-means clustering is simple and one of the most widely used clustering algorithm. [12] It is calculation wise very fast than the other algorithms. [13] It provides distinct results for distict no. of clussters. So it needs to be load the appropriate no. of clusters. It divides a given set of data into k number of disjoint clusters. [14] Suppose there is an image of resolution of x*y and we have to segment the image into k no. of clussters. Suppose p(i,j) is the pixel which has to be clustered and ck be the cluster's centeroid. [15] The k-means cluster algorithms is as below:

A.Initialise the no. of clusters k and their respective centroid.

B.To every pixels of magnetic resonance image, compute the Euclideen distances D, within the centroid and each pixel of an image using the relation given below.

$D = ||p(i, j) - c_k||$

C. Select every pixel to the closest center on the basis of distances D.

D. When every pixel assigned to the corresponding clusters then again compute the new location of the centroids.

E. Repeat the method til it entertain the value less than the predefined threshold. [16]

F. Transmute the pixel values into an image.

3.3 Bio-medical image segmentations with fuzzy c-means clustering

IMAGE SEGMENTATION is partition of an image into multiple meaningful (easier to examine) partitions or segments. Bio-medical image segmentation partitions the pixels in different regions like glioma and brain tumor. The Pixels in each segments share common property (ex: pixel intensity). It gives a correct diagnosis by evaluating brain tumor

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[19] [20] The FCM algorithm is a repeated algorithm of clustering technique that outturn optimal c partitions and centers K=k1, k2,, kc which are criterion, and radii which represents these K partitions. Let unlabelled data set P=p1, p2,, pn are pixels intensities where n is no. of pixels in an image. [21] The Fuzzy C-means algorithmes seeks to segment these pixels P in c no. of clusters. Conventional FCM evaluation functions is defined below:

$$F_m(I,J) = \sum_{x=1}^{c}\sum_{y=1}^{n} u_{ik}^{m} d^2(p_k, k_i) \tag{3.1}$$

where $d(p_y, k_x)$ denotes the separation between the pixel p_x and center k_x, along with constraint $\sum_{i=1}^{c} u_{xy} = 1$ and the degree of fuzziness $m \geq 1$.
A data point p_k belongs to a specific cluster k_i that is given by the membership value u_{ik} of the data point to that cluster. Local minimization of the objective function $F_m(I,J)$ is accomplished by repeatedly adjusting the values of u_{ik} and k_i according to the following equations:

$$u_{ik} = [\sum_{1}^{c}(\frac{d^2(p_k, k_i)}{d^2(p_k, k_j)})^{1/m-1}]^{-1} \tag{3.2}$$

$$k_i = \frac{\sum_{k=0}^{n} u_{ik}^{m} p_k}{\sum_{k=0}^{n} u_{ik}^{m}}, 1 \leq x \leq c \tag{3.3}$$

As F_m is repeatedly minimized, k_i becomes strong saturate. Repetition of pixels groups is eliminated while elimination measures $maximum||k_i^t - k_i^{t-1}|| < \epsilon$ is satisfied, where k_i^t is new centers, k_i^{t-1} is preceding centre, and ϵ is the predesigned elimination point.

3.3.1 Cluster Performance function

To calculate the fuzzy c-means segmentation performance quantitatively,we introduced the cluster performance function i.e. fuzzy partition of data set. The performance function is defined as follows:

$$V_{pf}(I) = \frac{\sum_{j=1}^{n} \sum_{i=1}^{c} u_{ij}^2}{n} \tag{3.4}$$

where, V_{pf} is partition function When V_{pf} is maximum, the optimal clustering is accomplished.

Chapter 4

Results and Disscusion

4.1 Description of Dataset and Results

In this experiment, the dataset which is from MICCAI BRATS challenge for the year of 2017 have been used.This Dataset consists of two-dimensional Magnetic resonance cerebrum images from very-high grade glioma patients. Image smoothing is done by median filtering, wiener filering and anisotropic filtering. For median filtering, a mask of 3*3 is used for some images and a mask of 5*5 is used for other images depending on the optimum mask size for that image. Figures 4.1 shows four actual cerebrum magnetic resonance images and figure 4.2 show anisotropic filtered images. For anisotropic filtering we have used no. of iteration=10, delta value=1/7, and kappa value= 15. These values are obtained by varying any one value and making all other values fixed and then chek the resulting image and the value at which resulting image is best is considered as optimum value. By similar process other parameters of anisotropic filtering are obtained.

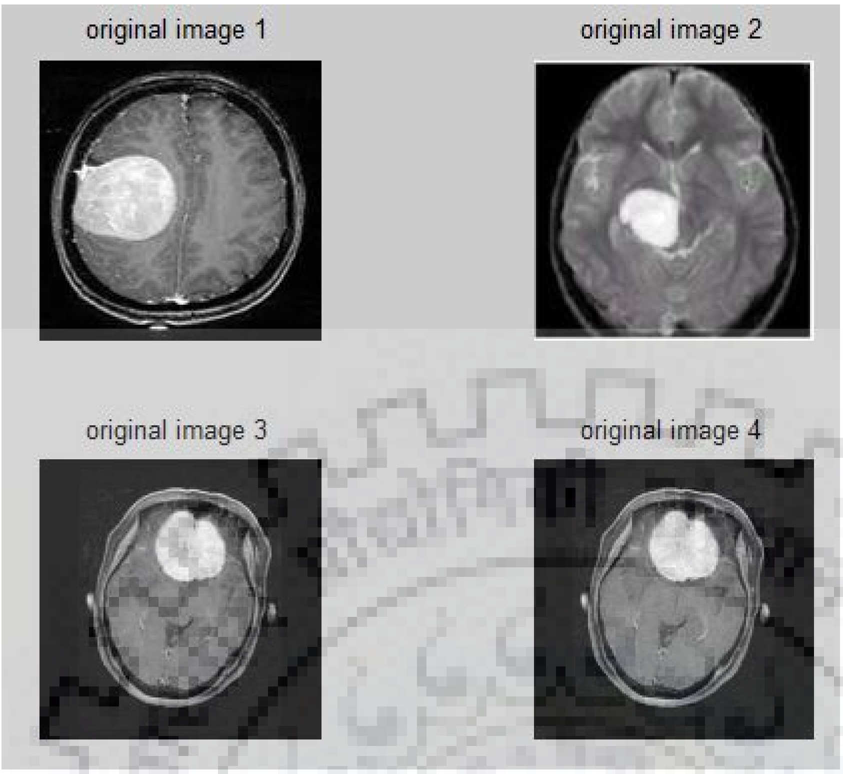

Fig. 4.1. Four actual cerebrum magnetic resonance images.

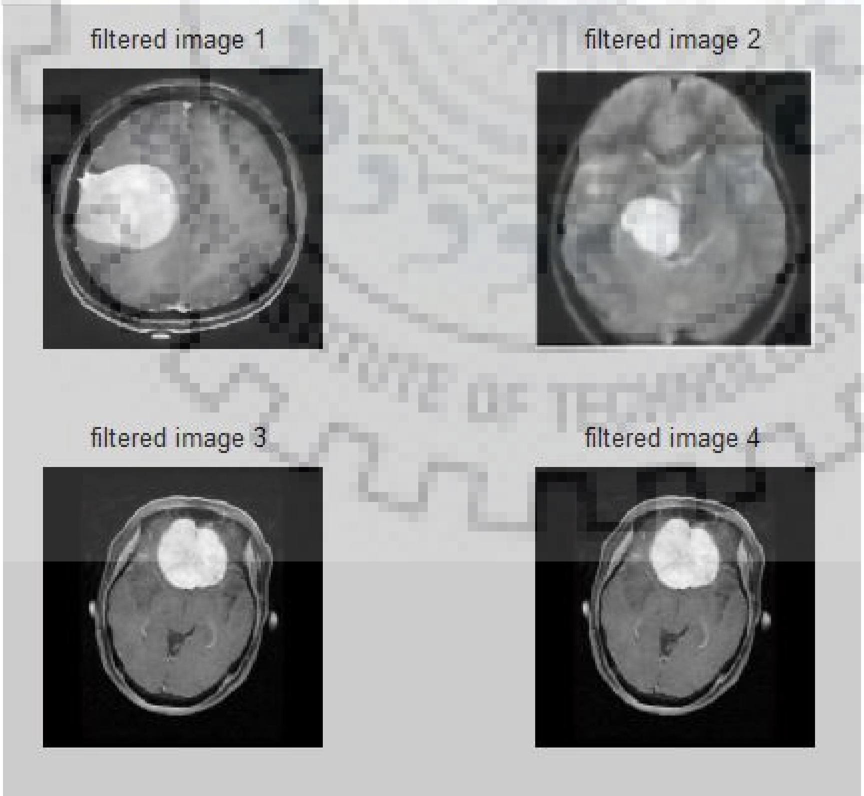

Fig. 4.2. Four anisotropic filtered cerebrum magnetic resonance images.

Figure 4.3 shows first actual cerebrum magnetic resonance image from MICCAI BRATS challenge for the year of 2017, filtered image and segmented image by using k-means clustering method. For k-means clustering, the number of cluster is taken as 5, and centroid for clusters are taken by calculating the step size of the image and then first centroid taken as minimum pixel value,second centroid is taken as (first centroid + step size), (third centroid = second centroid + step size), (fourth centroid = third centroid + step size), (fifth centroid = fourth centroid + step size). The centroid are continuously updating untill the new centroid becomes equal to the previous centroid.In this image noise is very less so k-means clustring gives accurate result of detected tumor.

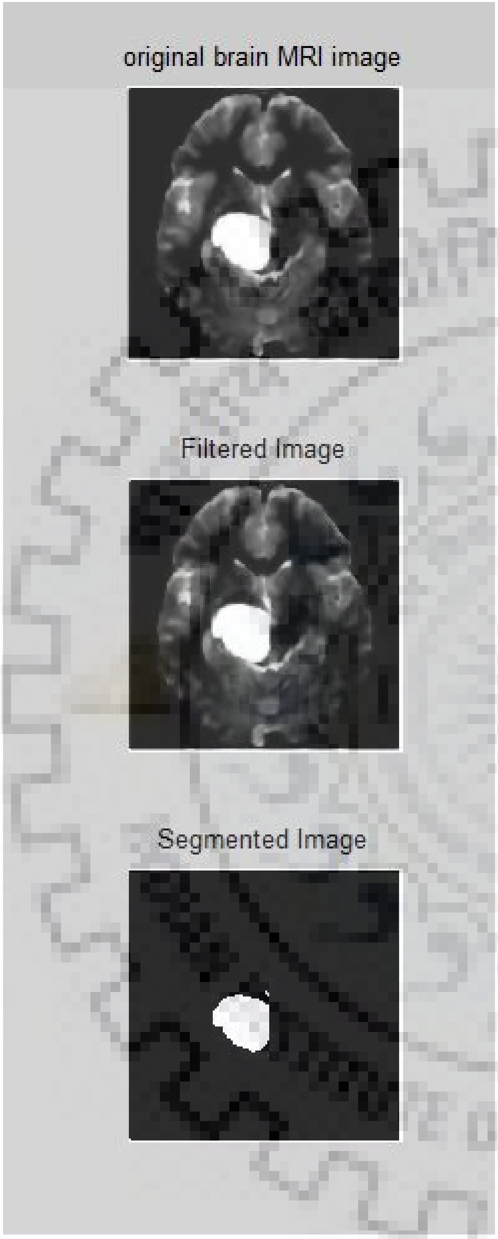

Fig. 4.3. Actual cerebrum magnetic resonance image, Filtered image and Segmented image.

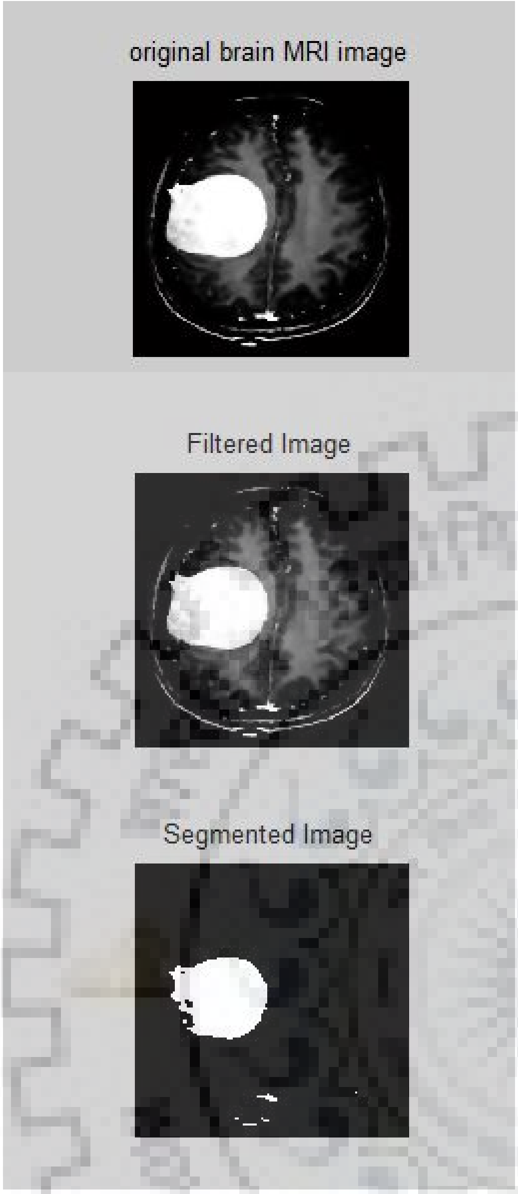

Fig. 4.4. Actual cerebrum magnetic resonance image, Filtered image and Segmented image.

Figure 4.4 shows original tumor MRI image of brain from MICCAI BRATS challenge for the year of 2017, filtered image and segmented image by using k-means clustering method. Here, the number of cluster is taken as 4 and centroid for clusters are taken by calculating the step size of the image and then first centroid taken as minimum pixel value,second centroid is taken as (first centroid + step size), (third centroid = second centroid + step size), (fourth centroid = third centroid + step size). In this image, high level of noise is present at bottom of the image so, little bit noise is detected as tumor although most of noise part is removed by filtering.

Figure 4.5 shows magnetic resonance image of brain from MICCAI BRATS challenge for the year of 2017, filtered image and segmented image by using k-means clustering method. Some part of tumor is not detected properly, because of high blurred image.But maximum part of the tumor is detected correctly. The number of cluster is taken as 5 and centroid for clusters are taken by calculating the step size of the image and then first centroid taken as minimum pixel value,second centroid is taken as (first centroid + step size), (third centroid = second centroid + step size), (fourth centroid = third centroid + step size),and (fifth centroid = fourth centroid + step size).

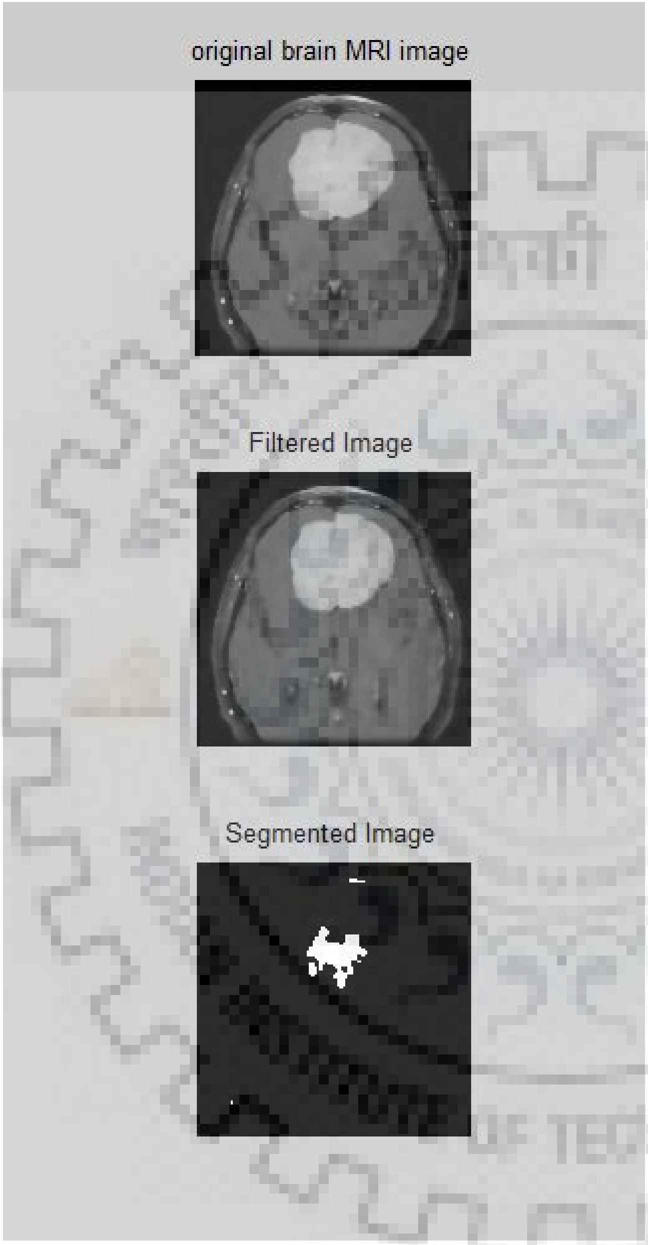

Fig. 4.5. Actual cerebrum magnetic resonance image, Filtered image and Segmented image.

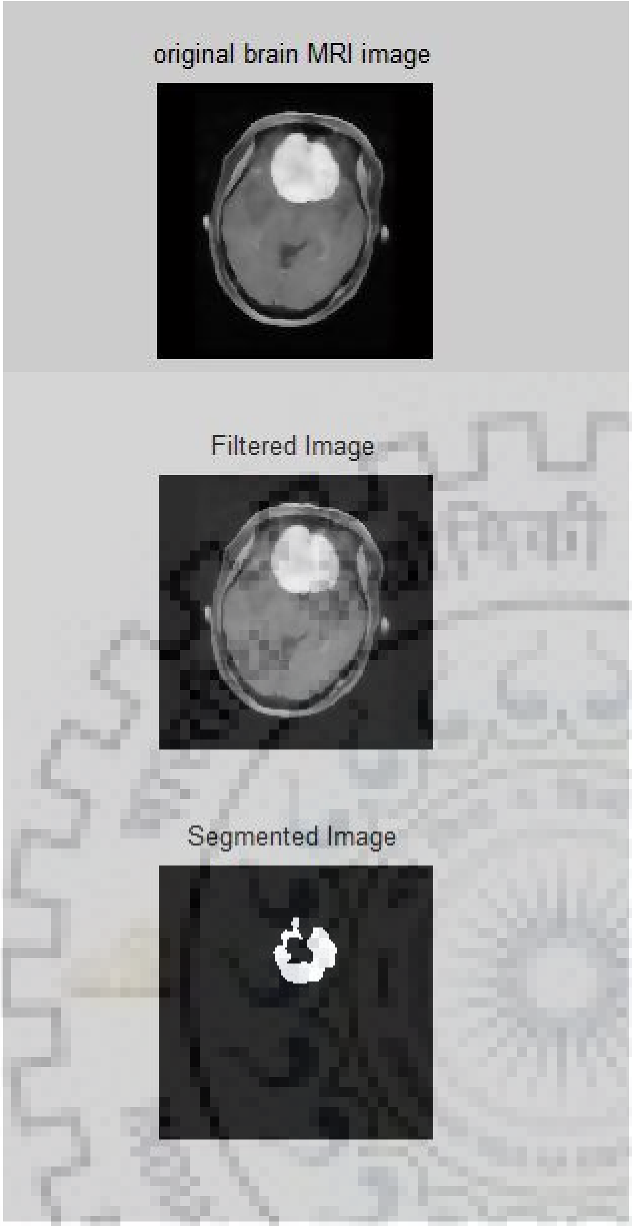

Fig. 4.6. magnetic resonance image, Filtered image and Segmented image.

Figure 4.6 shows tumor image from MICCAI BRATS challenge for the year of 2017, filtered image and segmented image by using k-means clustering method. The number of cluster is taken as 6 and centroid for clusters are taken by calculating the step size of the image and then first centroid taken as minimum pixel value,second centroid is taken as (first centroid + step size), (third centroid = second centroid + step size), (fourth centroid = third centroid + step size), (fifth centroid = fourth centroid + step size), and (sixth centroid = fifth centroid + step size). At the center of tumor part, noise predominate due to which tumor would not get detected properly at the center.

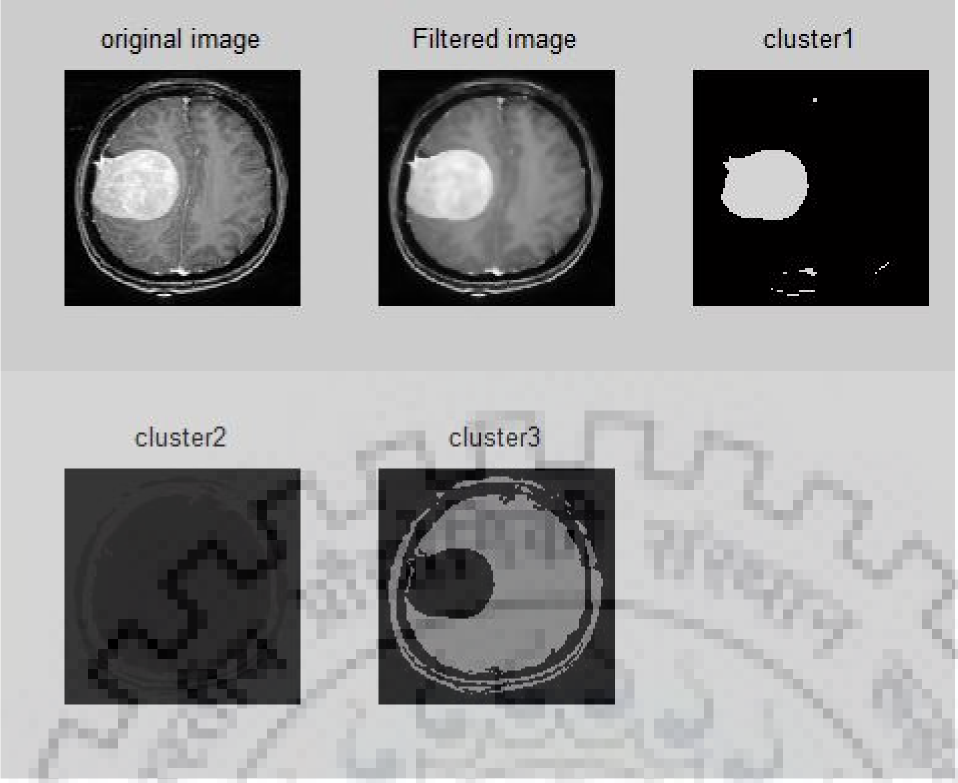

Fig. 4.7. Actual cerebrum magnetic resonance image, Filtered image and clusters using FCM with 3 clusters.

Figure 4.7 shows original cerebrum magnetic resonance image, filtered image, cluster 1, cluster 2, cluster 3 and cluster 4 images using fuzzy C-means clustering method. In fuzzy c- means clustering method,first image is filtered with anisotropic diffusion filter in which we have used no. of iteration=10, delta value=1/7, and kappa value= 15. These values are obtained by varying any one value and making all other values fixed and then cheking the resulting image and the value at which resulting image is best is considered as optimum value. By similar process other parameters of anisotropic filtering are obtained. And then image is resized to 256*256 pixels and taken only green pixel values. Here, number of clusters taken are 4.And then pixel is allocated to that cluster for which given cluster has maximum membership value. Tumor is detected accurately in this image.

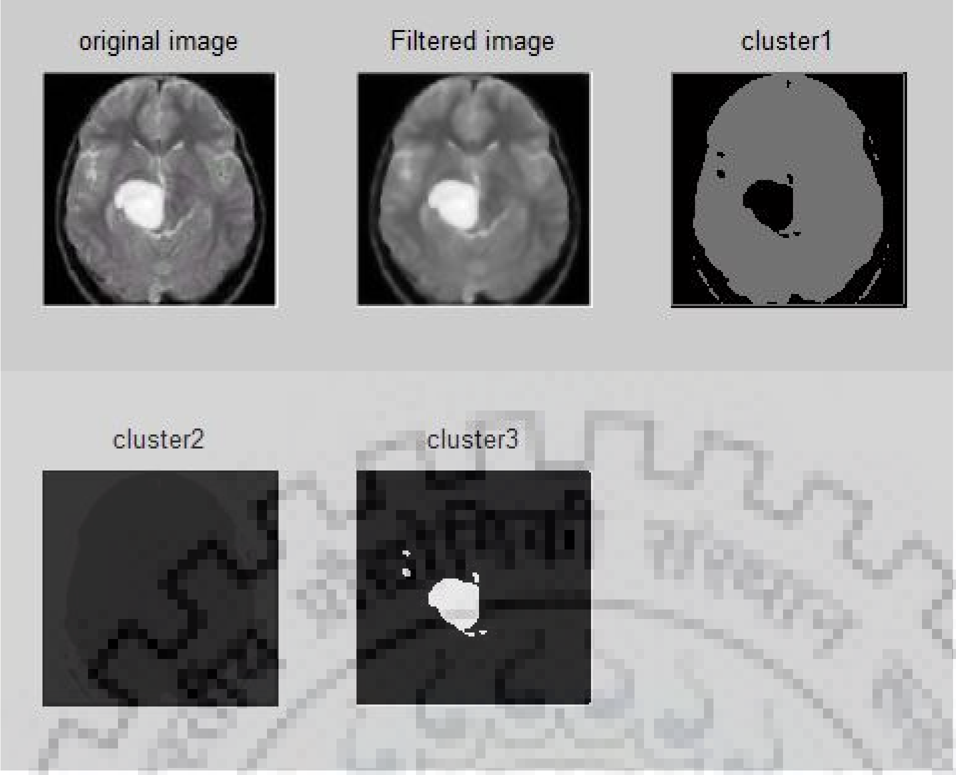

Fig. 4.8. Actual cerebrum magnetic resonance image, Filtered image and clusters using FCM with 3 clusters.

Cerebrum magnetic resonance image from MICCAI BRATS challenge for the year of 2017, filtered image, cluster 1, cluster 2, and cluster 3 using fuzzy C-means clustering method are shown in figure 4.8. Image is filtered with wiener filter and anisotropic diffusion filter in which we have used no. of iteration=15, delta value=1/8, and kappa value= 14. These values are obtained by varying any one value and making all other values fixed and then cheking the resulting image and the value at which resulting image is best is considered as optimum value. By similar process other parameters of anisotropic filtering are obtained. And then image is resized to 256*256 pixels and taken only green pixel values. Here, number of clusters taken are 3.

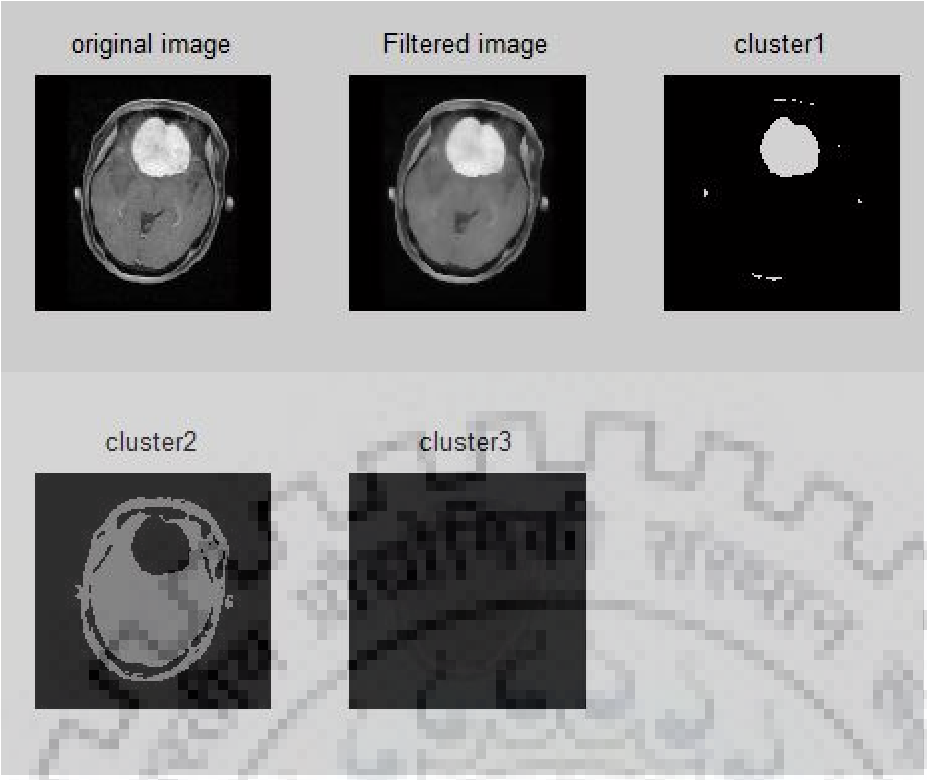

Fig. 4.9. Actual cerebrum magnetic resonance image, Filtered image and clusters using FCM with 3 clusters.

Figure 4.9 shows tumor magnetic resonance image from MICCAI BRATS challenge for the year of 2017, filtered image, cluster 1, cluster 2, and cluster 3 images using fuzzy C-means clustering method. In fuzzy c- means clustering method,first image is filtered with anisotropic diffusion filter in which we have used no. of iteration=20, delta value=1/9, and kappa value= 12. Here, number of clusters taken are 3.In this image there is some noise at outer boundary which is not fully removed by filter. It is detected as tumor in final image.

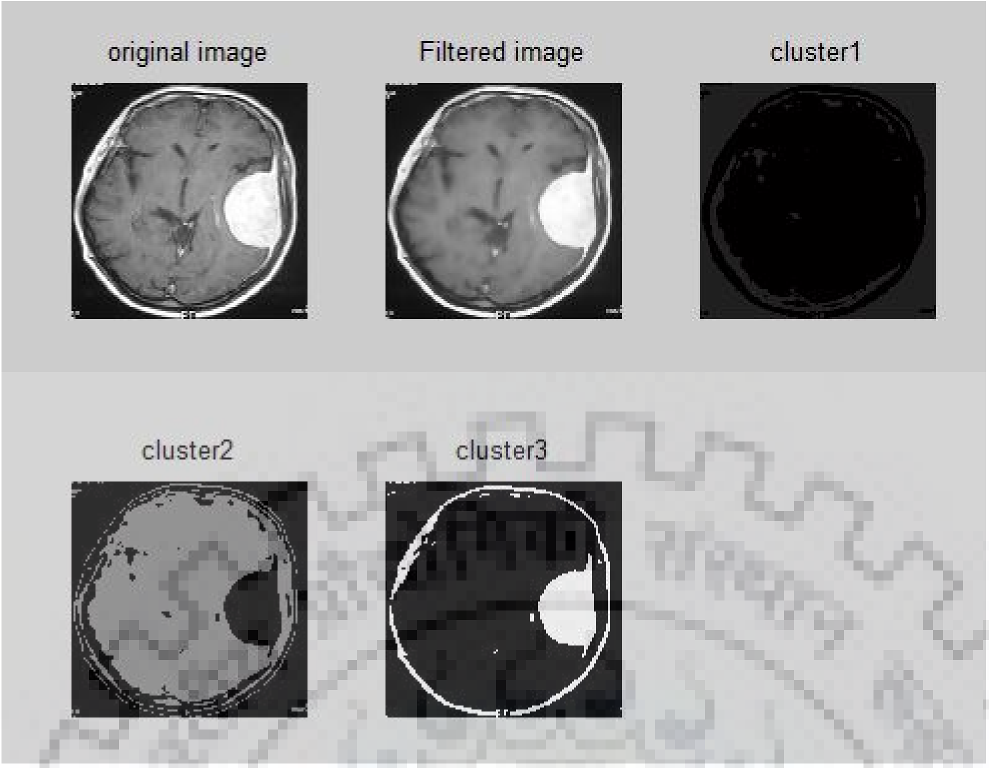

Fig. 4.10. Actual cerebrum magnetic resonance image, Filtered image and clusters using FCM with 3 clusters.

Brain magnetic resonance image from MICCAI BRATS challenge for the year of 2017, filtered image, cluster 1, cluster 2, and cluster 3 using fuzzy C-means clustering method are shown in Figure 4.10. In fuzzy c- means clustering method,first image is filtered with anisotropic diffusion filter in which we have used no. of iteration=18, delta value=1/7, and kappa value= 16.Noise is present in outer boundary which could not be removed by fuzzy c-means clustering. But k-means clustering have good result for this image.

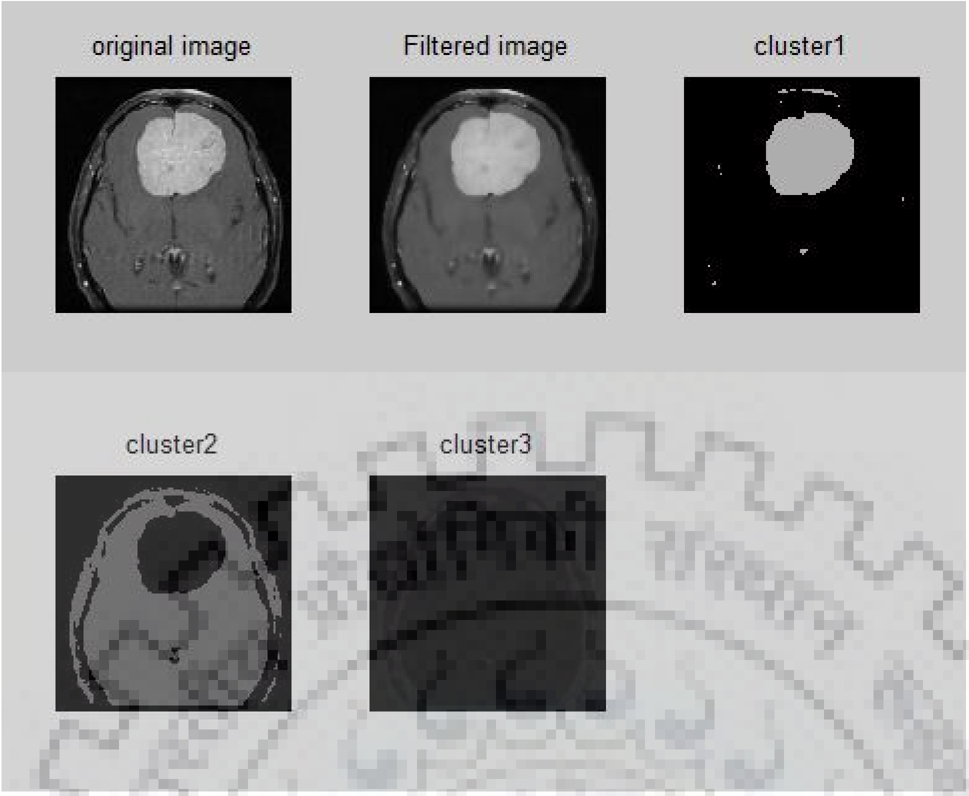

Fig. 4.11. Actual cerebrum magnetic resonance image, Filtered image and clusters using FCM with 3 clusters.

Tumor magnetic resonance image from MICCAI BRATS challenge for the year of 2017, filtered image, cluster 1, cluster 2, and cluster 3 are shown in figure 4.11 using fuzzy C-means clustering method. Here, image is filtered with three filters which are median filter ,wiener filter and anisotropic diffusion filter. For anisotropic filtering we have used no. of iteration=15, delta value=1/8, and kappa value= 13. Here,optimum result is obtained when we take number of clusters =3. Tumor is detected correctly in this image.

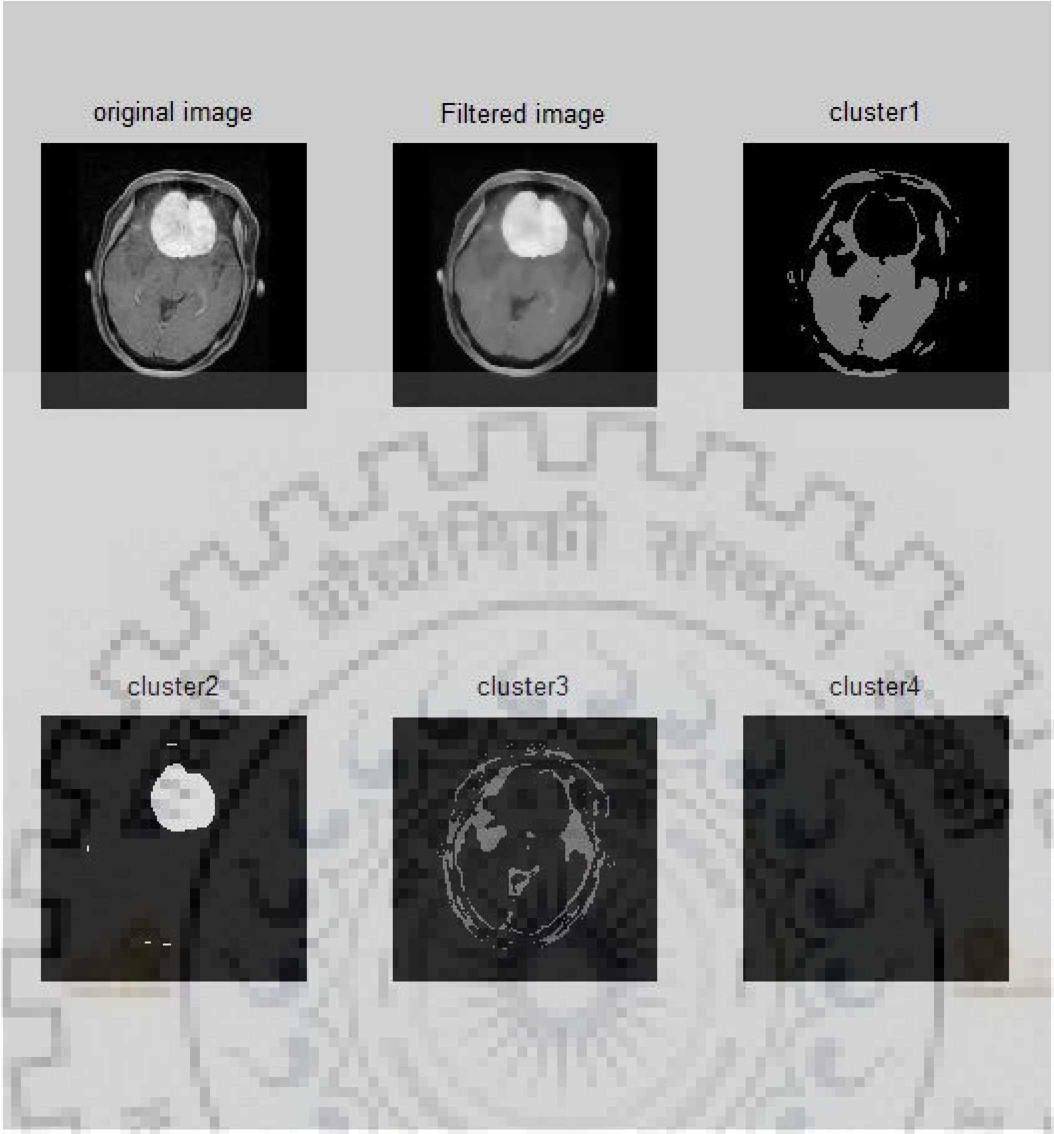

Fig. 4.12. Actual cerebrum magnetic resonance image, Filtered image and clusters using FCM with 4 clusters.

Figure 4.12 shows brain magnetic resonance image from MICCAI BRATS challenge for the year of 2017, filtered image, cluster 1, cluster 2, cluster 3, and cluster 4 images using fuzzy C-means clustering method. In fuzzy c- means clustering method,first of all image is filtered with anisotropic diffusion filter in which we have used no. of iteration=20, delta value=1/9, and kappa value= 14. Here, optimum result is obtained when we take number of clusters =4. Since original image has very less noise and clear boundaries so, tumor is detected accurately.

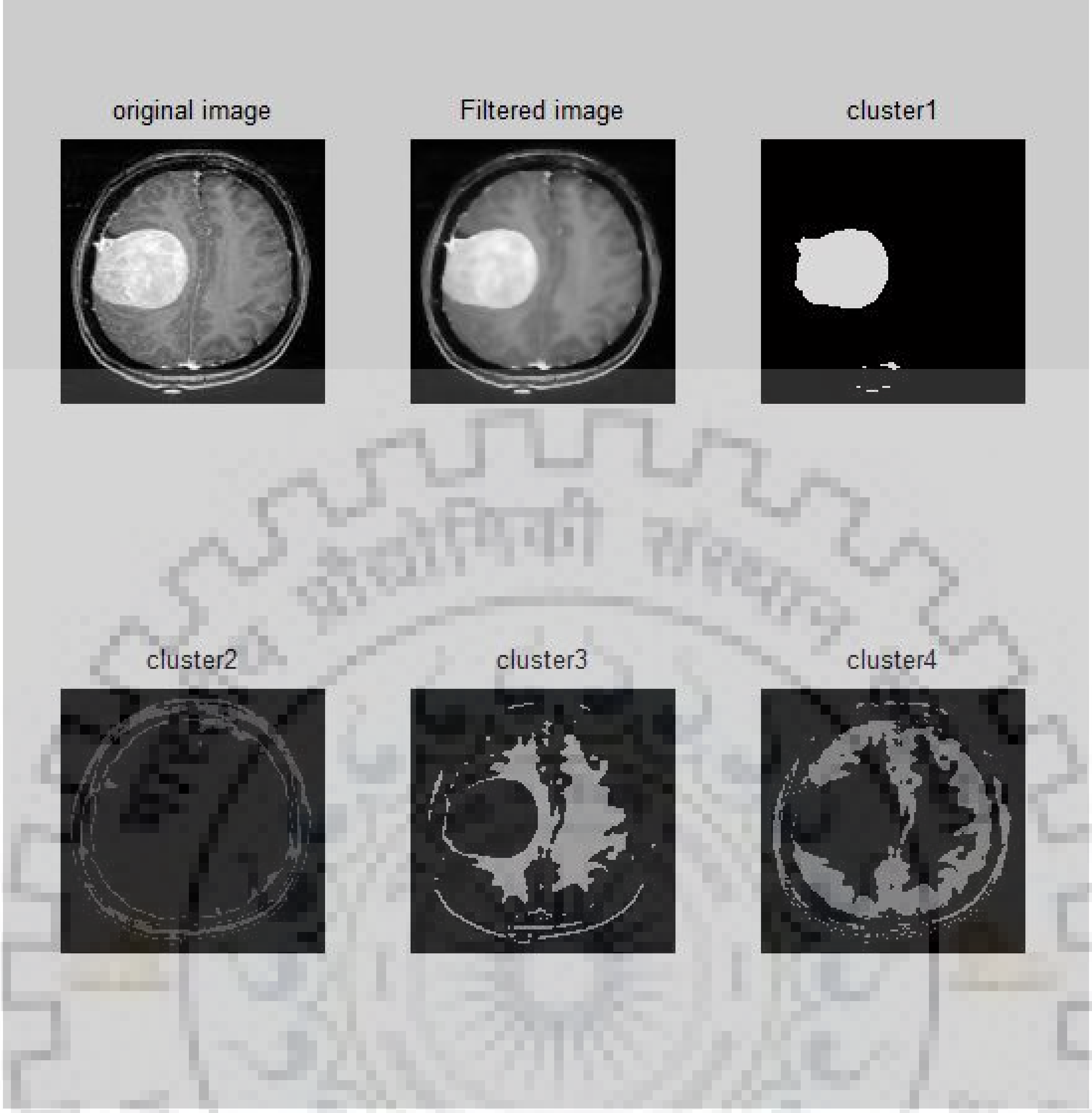

Fig. 4.13. Actual cerebrum magnetic resonance image, Filtered image and clusters using FCM with 4 clusters.

Tumor MRI from MICCAI BRATS challenge for the year of 2017, filtered image, cluster 1, cluster 2, cluster 3, and cluster 4 images using fuzzy C-means clustering method is shown in figure 4.13. Image is filtered with anisotropic diffusion filter in which we have used no. of iteration=18, delta value=1/8, and kappa value= 16 and then image is filtered with wiener filter to reduce blurring. Here, optimum result is obtained when we take number of clusters =4. Tumor is detected perfectly in this image.

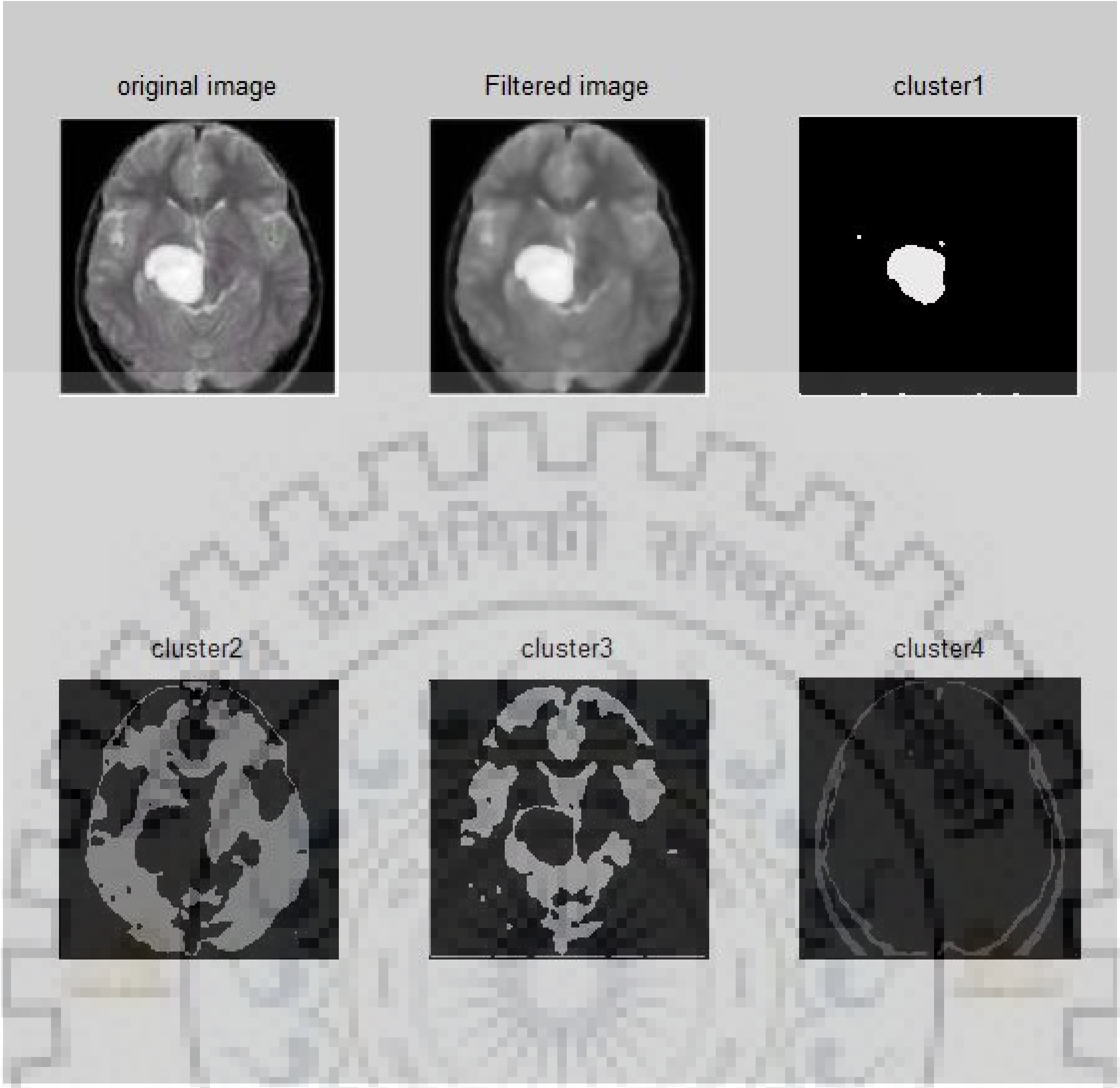

Fig. 4.14. Actual cerebrum magnetic resonance image, Filtered image and clusters using FCM with 4 clusters.

Figure 4.14 shows cerebrum magnetic resonance image from MICCAI BRATS challenge for the year of 2017, filtered image, cluster 1, cluster 2, cluster 3, and cluster 4 images using fuzzy C-means clustering method. Tumor is detected accurately by FCM method for this mri image. In fuzzy c- means clustering method,first of all image is filtered with anisotropic diffusion filter in which we have used no. of iteration=17, delta value=1/9, and kappa value= 15. Here, optimum result is obtained when we take number of clusters =4. Tumor is detected accurately by FCM method.

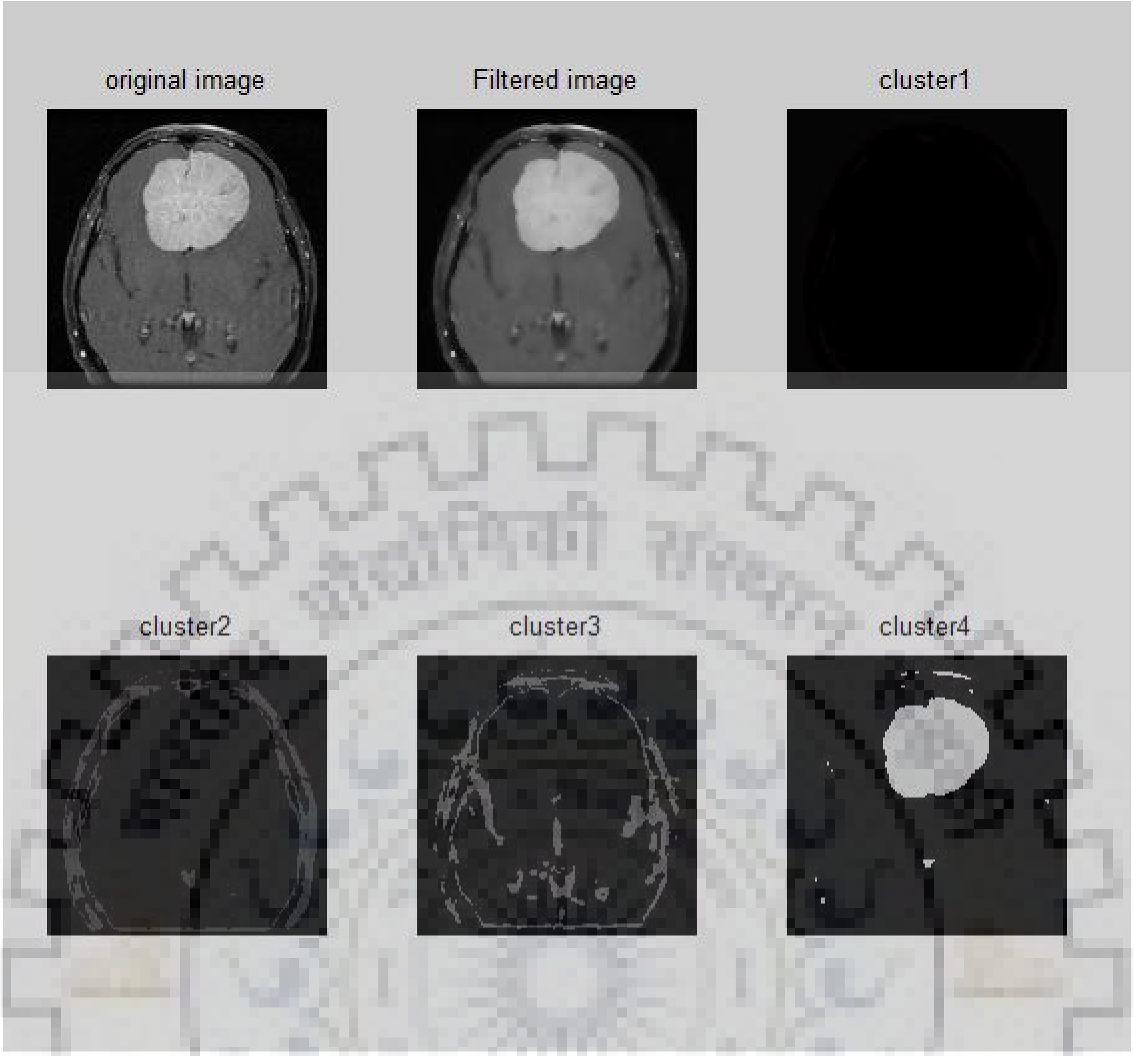

Fig. 4.15. Actual cerebrum magnetic resonance image, Filtered image and clusters using FCM with 4 clusters.

Tumor cerebrum magnetic resonance image from MICCAI BRATS challenge for the year of 2017, filtered image, cluster 1, cluster 2, cluster 3, and cluster 4 images using fuzzy C-means clustering method is shown in figure 4.15. Here, optimum result is obtained when we take number of clusters =4. Since noise spikes are present in an image, some noise part are present in output image. For filtering we used wiener filtering and median filtering.Median filtering removes salt and pepper noise very effectively from this image.

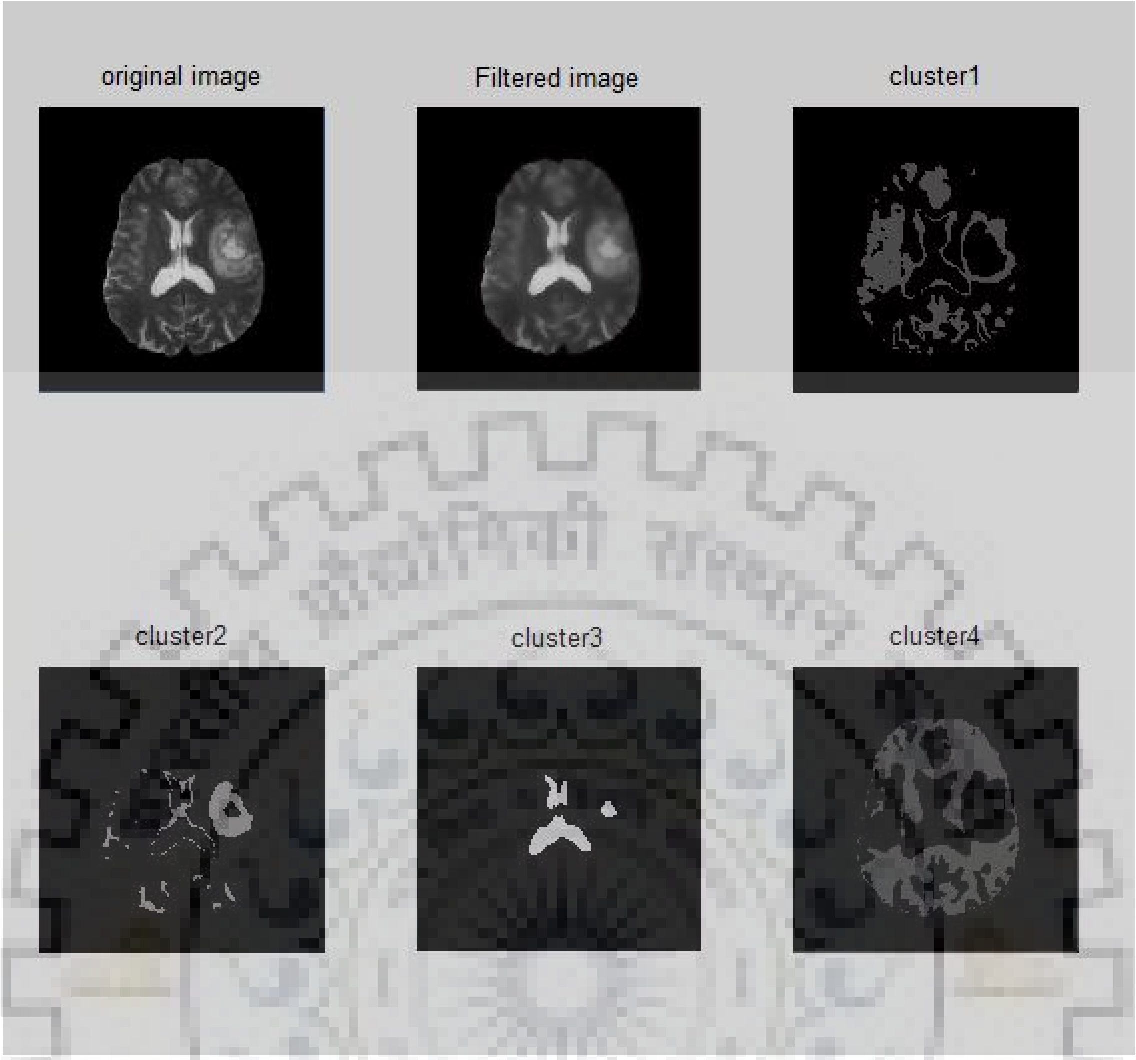

Fig. 4.16. Actual cerebrum magnetic resonance image, Filtered image and clusters using FCM with 4 clusters.

Figure 4.16 shows cerebrum MRI from MICCAI BRATS challenge for the year of 2017, filtered image, cluster 1, cluster 2, cluster 3, and cluster 4 images using fuzzy C-means clustering method. In this image tumor intensity is not uniform that means there is noise in the center of tumor. Here, optimum result is obtained when we take number of clusters =4. We have used no. of iteration=15, delta value=1/9, and kappa value= 14 for anisotropic filtering. Also blurring is present.To remove blurring anti-blurring filter has been used to amplify high frequency component.

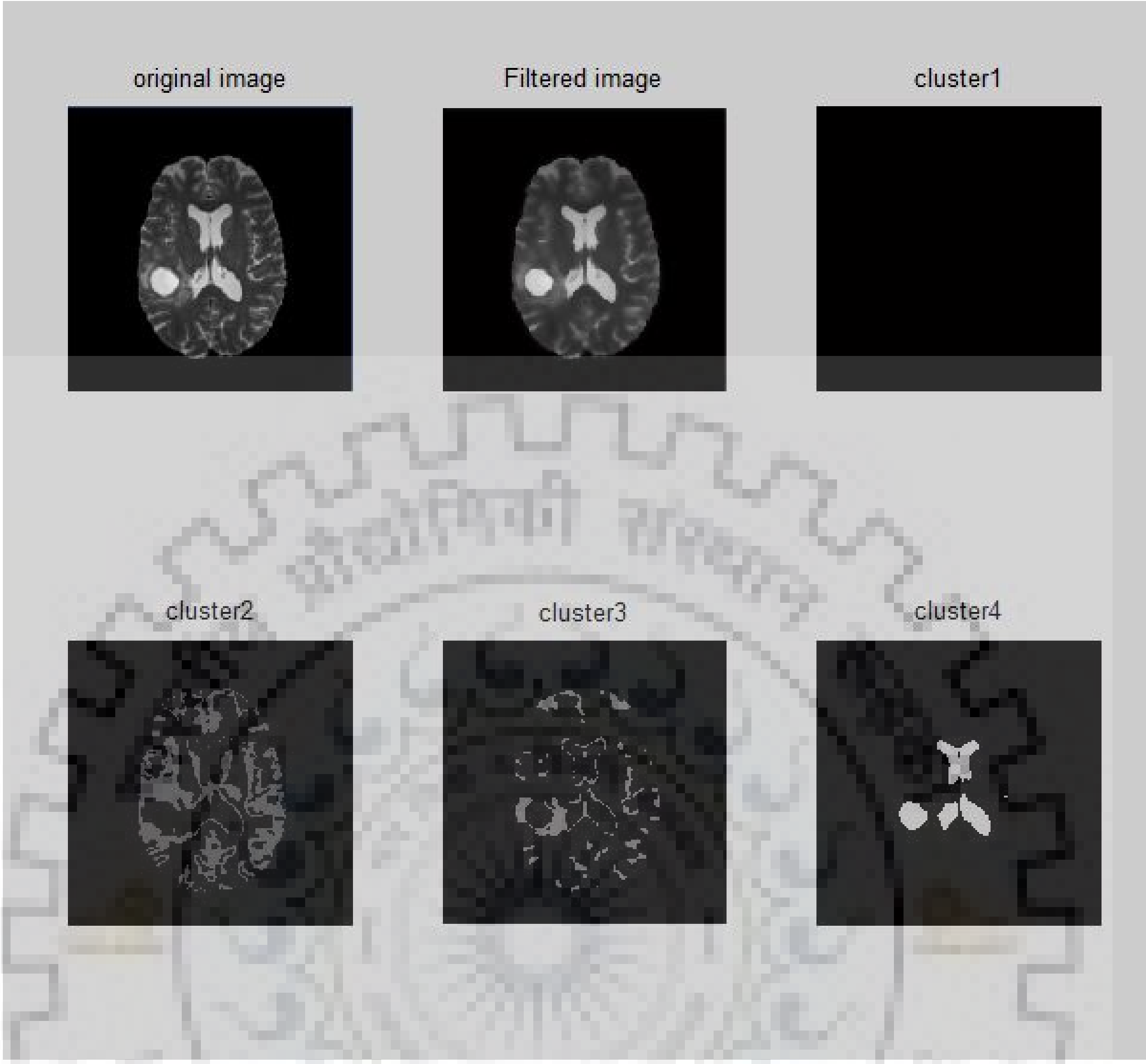

Fig. 4.17. Actual cerebrum magnetic resonance image, Filtered image and clusters using FCM with 4 clusters.

Brain MRI from MICCAI BRATS challenge for the year of 2017, filtered image, cluster 1, cluster 2, cluster 3, and cluster 4 images using fuzzy C-means clustering method are shown in figure 4.17. First of all image is filtered with anisotropic diffusion filter in which we have used no. of iteration=14, delta value=1/7, and kappa value= 12. Median filter is used to remove high intensity noise. Here, optimum result is obtained when we take number of clusters =4. In this image, noise spikes are also present. To remove these spikes we use median filter.

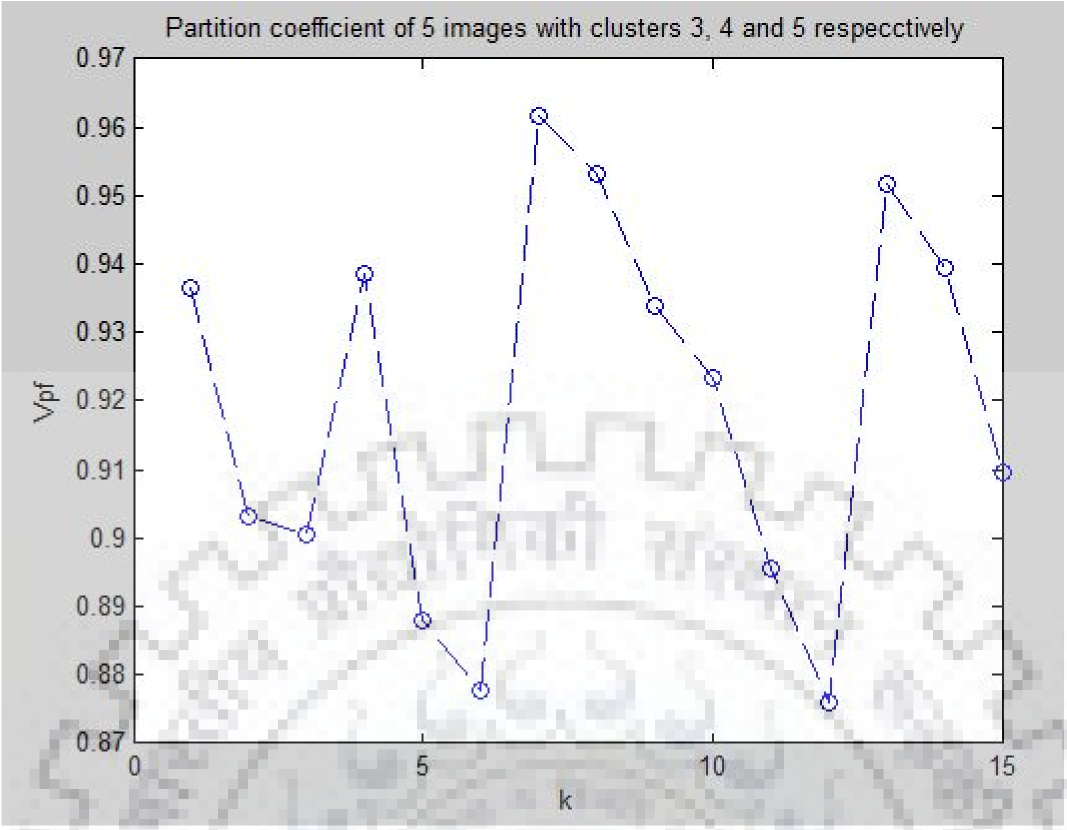

Fig. 4.18. Partition coefficient(Vpf) of 5 images with corresponding no. of clusters 3, 4 and 5

In this section, Performance of fuzzy c-means clustering method have been evaluated using five MRI two dimensional images from BRATS 2017 data set. Figure 4.18 shows the graph between Vpc (partial coeff.) and no. of clusters. The achievements of clustered algorithm has been calculated for different cerebrum magnetic resonance images on conditions of clusters performance functions. To every images, the weighted exponential $m = 1.5, \epsilon = 0.001$, and a 3x3 square S_k of the brain image pixels has been used. Partition-coefficient is calculated for every image by taking number of clusters three,four and five. According to partition coefficient values,for most of the medical images, optimum resuls are obtained when number of clusters taken as three. And when we increase the number of clusters beyond three, the values of partition-coefficient reduces.

Chapter 5

CONCLUSION AND FUTURE SCOPE

The K-means clustering and FCM algorithms are implemented for segmentation of the brain tumor for the dataset from MICCAI BraTs challenge. It has been observed that k-means clustering algorithm speed is faster than fuzzy c-means in most of the datasets. In fuzzy C-means clustering algorithm, there is more number of fuzzy calculations, therefore its execution time found relatively higher as compared to k-means clustering method. An important component for choosing right clustering method is the pattern of clusters in datasets to be anlaced. Discrepancies in fuzzy C-Means and K-Means were found in almost all groups except for different models.Optimum results are obtained for different no. of clusters in different images. For most of the MICCAI Brats challenge's images optimum results are obtained when number of clusters is taken as 3. However, their performances were found very good for circular and rectangular patterns as compared to ellipsoidal patterns, K-means clustering was found comparatively good. Further experimental studies should be conducted to clarify this finding by using other forms of distance norms like Manhattan and by applying the derivative algorithms of K-means and fuzzy c-means clustering. Sivarathri Govardhan (2014) had revealed that fuzzy c-means is better than K-means in term of accuracy of clusters on the diabetes dataset obtained from the UCI repository. However, in our study, neither K-means nor Fuzzy C-means were fruitful to find the incurvate and other kind of discretionary shaped clusters when they are not well separated. The conventional Fuzzy C-means algorithm based on pixel characteristic lead to accuracy degradation with segmentation because medical images have limited spatial resolution, poor contrast, high noise, and non-uniform intensity fluctuation. To overcome this problem, we have introduced a spatial fuzzy c-means (SFCM) algorithm that considers both pixel characteristics and the spatial local information which is weighted corresponding to neighbour elements based on their distance characteristics. This improves the segmentation performance.

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