ECG ANALYSIS AND HEART DISEASE CLASSIFICATION

A THESIS

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

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ELECTRICAL ENGINEERING

by

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in this thesis entitled "**ECG ANALYSIS AND HEART DISEASE CLASSIFICATION"** in partial fulfilment of the requirements for the award of the Degree of Doctor of Philosophy and submitted in the Department of Electrical Engineering of the Indian Institute of Technology Roorkee, Roorkee is an authentic record of my own work carried out during a period from July, 2009 to June, 2016 under the supervision of Dr. Vinod Kumar, Professor, Department of Electrical Engineering, Indian Institute of Technology Roorkee, Roorkee and Dr. Ritesh Kumar, Associate Professor, Department of Cardiology, Rajendra Institute of Medical Sciences, Ranchi.

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.

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ABSTRACT

The heart is a vital organ in humans and animals which circulates blood through blood vessels in the whole body. The blood provides nutrients and oxygen to all cells, and removes wastes of metabolism. Heart disease is the main killer of men and women in the world; particularly in the United States, Canada, England, and Asian countries. The common diseases of the heart areheart attack (Myocardial Infarction), arrhythmias and sudden cardiac arrest. Therefore, early detection and accurate diagnosis are important issues in clinical practice of cardiologists and physicians.

The cardiologist or physician identifies heart diseases on the basis of ECG signals. The electrocardiogram (ECG) is a noninvasive method for detecting heart diseases. The ECG signal basically represents normal or abnormal functioning of heart activity. The normal ECG signal generally consists of P-wave, QRS-complex and T wave. The cardiologists and physicians have defined rules and definitions for visual ECG analysis, which may have subjectivity and are not uniform, so computer based interpretation is the need of this day. The ECG signal analysis and classification involve acquisition of ECG data, pre-processing of ECG signals, detection of ECG wave complexes such QRS complex, P & T-wave, etc. Next, their wave boundaries such as P_{onset}-P_{offset}, QRS_{onset}-QRS_{offset} and T_{end} are found and then clinical relevant intervals, such as P duration, duration of QRS complexes, ST-T interval and QT interval along with morphologies of each wave are determined. On the basis of ECG wave complexes, amplitude and wave interval features are extracted for classification. The aim of the present work is to do ECG analysis using simple approaches and then improve diagnostic performance.

Recorded ECG signals contain noises and artifacts such as power line noise, baseline wander, motion artifacts, etc. In this work, removal of baseline wander and motion artifacts has been implemented for detection of QRS complexes. The second stage is detection of QRS complexes and wave components. Here, QRS complex detection of single and multilead ECG signals has been done by proposing a new algorithm. The detection of P and T wave has also been implemented in multilead ECG signals. The clinical parameters in ECG signal are calculated on the basis of boundary marking of P-QRS-T complexes, so marking boundaries of ECG wave complexes required accurate and reliable method. This has been achieved by proposed new algorithm. Diagnosis and classification of ECG signal required accurate and reliable method. Here classification of Myocardial Infarction, Cardiomyopathy, and bundle branch block has been done using the detected diagnostic parameters.

Description of research work: The acquired raw ECG signal contains noises and artifacts. In this work we have developed a two stage median filter to remove baseline

wander using window width size $f_s/2$ and f_s for stage first and second in terms of sampling frequency (f_s).

Single lead QRS detection: A simple and efficient new method for QRS detection in the ECG is proposed in this research work. The initial data is preprocessed using two stage median filter for removing baseline drift. The second stage, enhances the peaks of ECG wave components by using the sixth power of the signal. The next stage identifies the QRS complex by taking a variable window size. The performance of the new algorithm is evaluated against the CSE, MIT/BIH AD, ESC ST-T and QT databases. These four standard databases were used to perform QRS detection and 368 cases were considered which were, tested on 10,06,168 beats and achieved overall average sensitivity 99.52% and positive predictivity of 99.69%. The QRS detection was also performed on 12 datasets of noisy, full length signals (118e24 to 118e_06 and 119e24 to 119e_06) from MIT–BIH Noise Stress Test Database and obtained performance is higher and comparable to other algorithms in literature.

Multilead QRS detection: QRS detection in 12-Lead Electrocardiogram (ECG) using composite lead and peak enhancement method is proposed in this thesis. Initially raw signals of 12-Lead electrocardiogram having a sampling frequency f_s are pre-processed for baseline wander removal using a two stage median filter with window widths of $f_s/2$ and f_s respectively. The point by point average of the preprocessed signals corresponding to 12-Leads is taken to generate a composite lead. In order to obtain a variable size search window for QRS detection, the composite lead is enhanced by the sixth power of the signal and its mean value is determined. The maximum value of the search space defined by the search window was mapped on the composite lead and other 12 ECG leads of 12-lead ECG individually for QRS detection. The performance of the algorithm is evaluated against the CSE multilead measurement database and St. Petersburg Institute of Cardiological Technic's 12-lead Arrhythmia Database and PTB Database. The overall performance of the proposed method, using different standard multilead databases, such as CSE, PTB and St-Petersburg multilead Arrhythmia with different cases and, total 2,55,925 beat was analyzed. The overall average sensitivity of 99.24% and positive predictivity of 99.90% was achieved considering all different standard databases.

Boundary marking of ECG wave components and diagnostic parameter detection: Boundary point's detection in simultaneously recorded 12-Lead ECG signal using a composite lead is proposed in this work. The complexes of the composite lead are better enhanced and noise free compared to others in any of the 12 lead signals. After detection of the QRS location of composite lead QRS_{onset} and QRS_{offset} were determined by using the standard deviation method. Detection of P-wave location and onset-offset was carried out by using the standard deviation method and similarly T wave location was determined, and T_{end}

was marked. The performance of the algorithm is evaluated against the CSE multilead database, the main boundary marking of P_{onset}, P_{offset}, QRS_{onset}, QRS_{offset} and T_{end} estimated are within limits recommended by the CSE working party. In this software we obtained unbiased measurement within specified limits.

For automatic ECG analysis and diagnosis system a dominant beat is required for measurements and classification. The onsets of P, QRS and offsets of P, QRS and T wave are detected on the composite beat and boundary values of the composite beat were mapped in all the average beats of 12-Leads. After determination of P duration, QRS complex duration, ST-T complex interval and QT interval, and other parameters such as peak to peak amplitude, area, mean, standard deviation, skewness and kurtosis of P duration, QRS duration and ST-T complex interval of all average beats of 12-lead ECG are calculated. In this work disease diagnosis and classification were performed using different ECG lead arrangements with SVM and ANN classifiers.

Detection of myocardial infarction has been performed using composite lead parameters and all 12 lead parameters with SVM and ANN classifiers and it is observed that ANN classifier obtained maximum accuracy in composite lead and all 12 lead systems. Also, it is observed that after reduction in dimensionality using PCA, obtained classification accuracy is 100% in both lead systems. Thus, it can be concluded that the composite lead system performed comparable and significant MI detection.

Detection of cardiomyopathy has been performed using twenty two features from composite lead and 220 features from all 12 lead with SVM and ANN classifier. In this case performance of cardiomyopathy detection is higher in ANN classifier for both composite lead and all 12 lead system and it is observed that after reduction of dimensionality using PCA, performance of SVM and ANN classifiers decreased in both lead systems. Thus, it can be finally concluded that cardiomyopathy detection using ANN classifier with a composite lead system performs better than SVM.

Detection of bundle branch block has been performed using extracted features of composite lead and all 12 Lead systems with SVM and ANN classifiers. In this study ANN classifier (accuracy with PCA: 80%, accuracy without PCA: 100%) performed better than SVM (accuracy with PCA: 68.75%, accuracy without PCA: 68.75%) with all 12 lead systems.

The Computer Assisted ECG Analysis and Classification system is designed for healthy, myocardial infarction, cardiomyopathy and bundle branch block with ANN classifier using composite lead and all 12 lead features. In this case, classification accuracy obtained is 100% with the composite lead system using PTB annotated database.

Thus, it can be finally concluded that the composite lead system contributes significantly for ECG analysis and classification systems. The overall work done in this thesis may be considered a positive and significant contribution in this field.

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The purpose of the CSE and Physonet Database (MIT/BIH Arrhythmia Database, MIT/BIH Noise Sterss, European ST-T Database, QT Database, St. Petersburg 12-Lead Arrhythmia Database, and PTB Database library, journal papers and books referred to my employment and help offered by the medical experts is greatly recognized.

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(Ashok Kumar Dohare)

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LIST OF ACRONYMS

AD	Arrhythmia Database
AHA	American Heart Association
AMI	Acute Myocardial Infarction
ANN	Artificial Neural Network
AV	Atrio Ventricular
BBB	Bundle Branch Block
BPM	Beats Per Minute
CM	Cardiomyopathy
CSE	Common Standards for Quantitative Electrocardiography
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
EMG	Electromyogram
ESC	European Society of Cardiology
FN	False Negative
FP	False Positive
FPA	Frontal plane Axis
HC	Healthy Control
HR	Heart Rate
HRV	Heart Rate Variability
KLT	Karhunen Loeve Transform
LA	Left Atrium
LBBB	Left Bundle Branch Block
LV	Left Ventricle
LVH	Left Ventricular Hypertrophy
MI	Myocardial Infarction
MIT/BIH	Massachusetts Institute of Technology/Beth Israel Hospital
PCA	Principal Component Analysis
PVC	Premature Ventricular Contraction
SVM	Support Vector Machine
TMT	Tread Mill Test
WT	Wavelet Transform

LIST OF SYMBOLS

I	Lead First
II	Lead Second
III	Lead Third
aVR	Augmented Lead Rightward
aVL	Augmented Lead Leftward
aVF	Augmented Lead Inferior
V1	Chest Lead First
V2	Chest Lead Second
V3	Chest Lead Third
V4	Chest Lead Fouth
V5	Chest Lead Fifth
V6	Chest Lead sixth
Hz	Power line frequency unit
dB	A logarithmic unit (Decibel)
V_X, V_Y, V_Z, X, Y, Z	Frank Lead
f_s	Sampling frequency
P_{onset}	P-wave onset
P_{offset}	P-wave offset
QRS_{onset}	QRS complex onset
QRS_{offset}	QRS complex offset
Tend	T-wave end
a	Mean value of signal for threshold
$y_p[n]$	Input Channel at p number
$x_p[n]$	Channel data value of p number
N	Total sample in channel
$x_{m1}[n]$	First stage median filter array
$x_{m2}[n]$	Second stage median filter array
$x_f[n]$	Filter output
$x_d[n]$	Enhanced signal
$A_v(k)$	Simultaneous space average value of 12 leads at a particular point
A_{CL}	Composite lead signal
a	Mean value of signal for threshold
$y_p[n]$	Input Channel at p number
$x_p[n]$	Channel data value of p number
N	Total sample in channel
$x_{m1}[n]$	First stage median filter array
$x_{m2}[n]$	Second stage median filter array
$x_f[n]$	Filter output

$x_d[n]$	Enhanced signal
$A_v(k)$	Simultaneous space average value of 12 leads at a particular point
A_{CL}	Composite lead signal
A_{CLE}	Enhanced composite signal
C	Best regularization parameter
γ	Best kernel parameter

CHAPTER 1: INTRODUCTION

This chapter explains the research work carried out in this thesis. It introduces the heart anatomy, the electrical conduction system of the heart, electrocardiogram, lead system, noise & artifacts in the recorded ECG signal, heart diseases, motivation, objectives of the present study and organization of the thesis.

1.1 Overview

The electrocardiograms (ECGs) are biological signals that originate from the muscles of the heart. These biological signals are basically the electrical signature of performance of the heart muscles that are either functioning normal or abnormal. These ECGs signals depict the health condition of the human body. Each ECG beat is represented by P-wave, QRS-complex and T-wave. On the basis of ECG signal observation and analytical thinking, experienced cardiologists or clinicians diagnose heart diseases. These diagnoses or marking of ECG signals become gold standards which are referenced for further analysis of other similar heart diseases. In the world, human population is increasing day by day, Number of physicians or clinicians are not sufficient to handle increasing number of patients, so computer based diagnosis is the need of the day. In present scenario for helping physicians or clinicians for fast diagnosis of heart diseases, automatic (computerized) ECG analysis is a must. Computerized ECG is generally of two types: computer assisted diagnosis and computer based monitoring of cardiac activities such as arrhythmias and ST-T changes. The computer assisted diagnostic system and monitoring started in last six decades. In this duration, many computer assisted diagnostic methods have been developed on the basis of different logic and methodologies [1-11].

1.2 The Heart Anatomy

Fig. 1.1 depicts the schematic structure of the heart. The human heart is a muscular organ which pumps blood through the circulatory system. The walls of the heart consist of the cardiac muscles, known as myocardium. The heart is composed of four chambers with two atria for collection of deoxygenated and oxygenated blood known as right and left atria, respectively, and two ventricles for pumping deoxygenated and oxygenated blood to the lungs and all body cells called right ventricle and left ventricle, respectively. The heart has four valves for the proper functioning of pumping process, the tricuspid valve between the right atrium and right ventricle, the mitral valve between the left atrium and left ventricle, the pulmonary valve between the right ventricle and the pulmonary artery, and aortic valve between the left ventricle and the aorta [12].

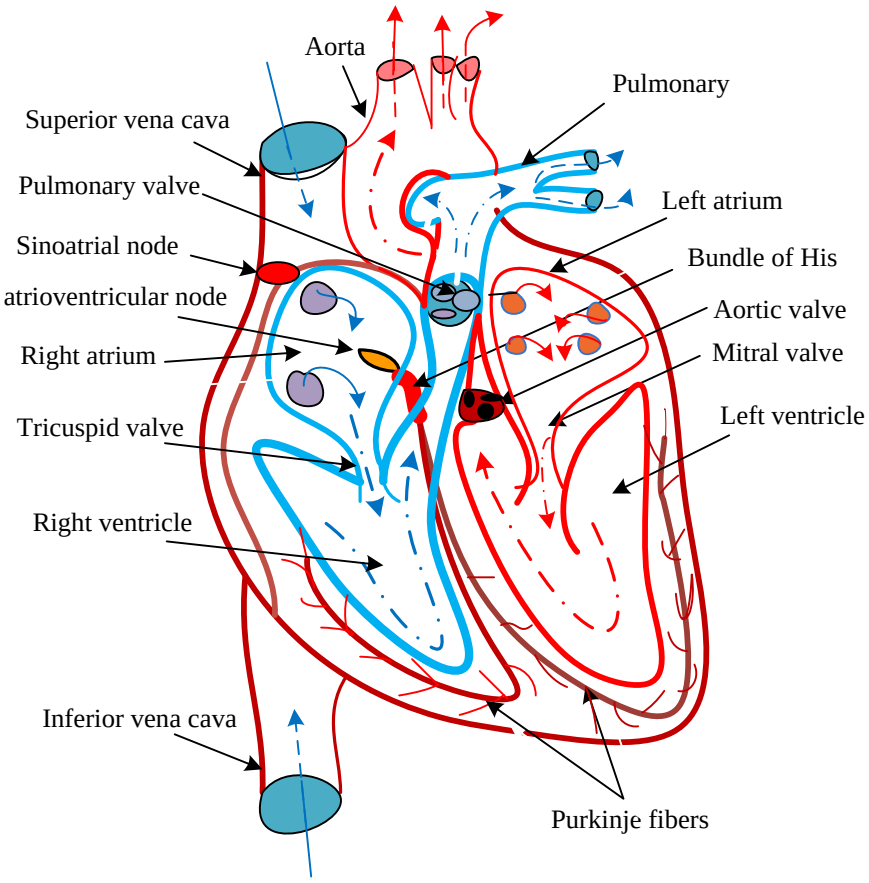

Fig. 1.1 Schematic structure of the heart

1.2.1 The Electrical Conduction System of the Heart

The electrical conduction is the major activity of the heart. It controls the rhythmic contractile activity of the heart. The *sinoatrial node* (SA node) is located in the right atrium close to the superior vena cava. This node is a group of self excitatory cells, and known as pacemaker cells. The *atrioventricular* node (AV node) is situated between atria and ventricles. The SA node generates excitation waves at the rate of about 70 pulses per minute. These waves propagate through the atria and reach the atrioventricular node, and its frequency is approximately 50 pulses per minute. From AV node, these wave propagates to the ventricles through bundle of His. bundle of His further splits into left bundle branches, right bundle branches and Purkinje system [13].

1.2.2 Electrocardiogram wave and its various components

The Electrocardiogram (ECG) is an electrical activity of the heart, and recording of the electric potential, on the body surface. The ECG wave is composed of three major waves, such as P wave, QRS complex, and the T wave, and two segments such as PR and ST segment. In ECG signal different wave intervals and segments are depicted in Fig. 1.2 and detailed descriptions are given below:

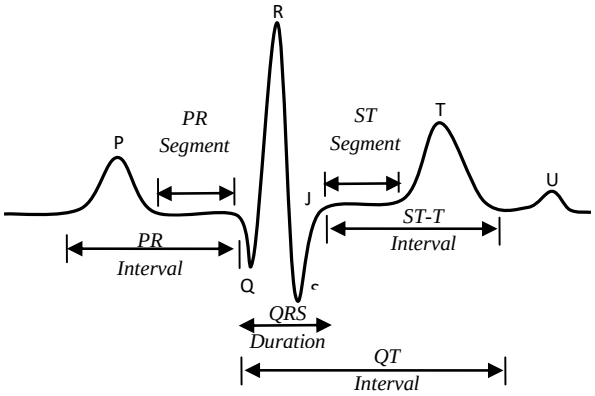

Fig. 1.2 Electrocardiogram and its various components

P wave: The initial part of P wave represents the electrical activity due to right atrium; the middle part of the P wave represents the completion of right atrial activation and initiation of left atrial activation; and the latter portion is generated due to left atrium. Its normal amplitude is about 0.1 - 0.2 mV.

P wave duration: It is the duration for the depolarization process of both atria, sequentially right and left atria, its duration is about 60 - 80 ms.

PR interval: The PR interval measures the time required for the atrial depolarization, through the AV node, bundle of His, bundle of branches, and Purkinje fibers up to start of depolarization of the ventricles. With normal conduction, the duration of this interval ranges from 120 to 200ms.

PR segment: PR segment represents the period from the end of P wave point to the onset of QRS complex; it is generally ISO-electric and, normally ranges from 40 to 160 ms.

QRS complex: The QRS complex represents the spread of electrical activation through the ventricular myocardium. The sharp, pointed deflections are labeled as QRS complex regardless of their sign (positive or negative).

QRS duration: It is defining the depolarization of the intraventricular septum and both ventricles sequentially i.e. from right and left. Its normal duration is about 60 to 120 ms.

T wave: The T wave represents electrical recovery of the ventricles and it goes from 200 to 300 ms after the QRS complex. It is sometimes merged with a P wave, and as a result, it becomes difficult to determine the end point of T wave. Its normal amplitude is about 0.1-0.3 mV.

T wave duration: The T wave duration is generally included in QT interval and its normal duration is about 120-160 ms.

ST segment: The ST segment represents the period when both ventricles are depolarized and the next stage of depolarization is started. Its normal duration ranges from 100 to 102 ms.

ST-T interval: The ST-T interval measures from the QRS complex offset to T end point.

QT- interval: It is measured from the QRS complex onset to T endpoint, and commonly there is a variation in the various leads. Its normal range is from 350 to 400 ms.

U wave: It is a small wave and takes after the T wave which is mentioned in some ECG records of some people. The U wave is basically monophasic and observed in healthy persons [14].

1.3 Lead System

In the ECG lead system, early researchers were divided into two groups - those who used simultaneously recorded XYZ leads and those who favoured the use of conventional 12-lead system. Physicians, mostly used 12-Lead ECG system. It consists of ECGs in groups of three leads simultaneously, such as I, II, III; aVR, aVL, aVF; V1, V2, V3; V4, V5, V6 or simultaneously recorded all 12-Leads [1]. The 12-Lead system arrangement is depicted in Fig. 1.3. The data recorded simultaneously by the 12-Leads is known as a multilead ECG data.

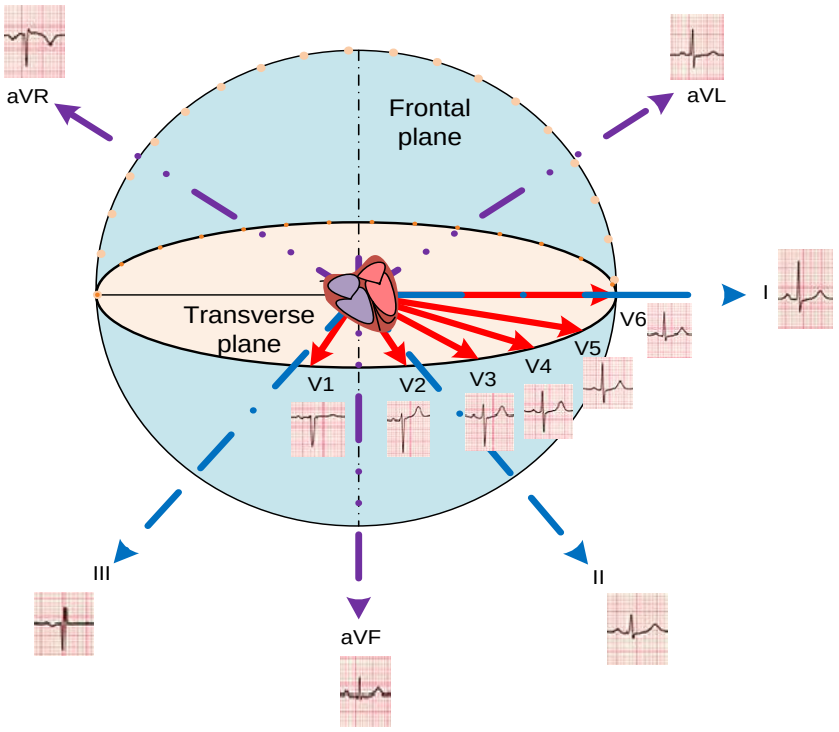

Fig. 1.3 12-Lead ECG arrangement system

The 12-lead ECG system consists of 10 electrodes. The electrodes in the main consist of conductive gel and Ag/AgCl sensing elements with self adhesive pad. The electrodes RA, LA, RL and LL are placed on the Right Arm, Left Arm, Right Leg, and Left Leg, respectively. These four electrode arrangements produce three bipolar limb leads - I, II, and III and three

unipolar augmented limb leads - aVR, aVL, and aVF. All above six limb leads are used to calculate the ECG signal axis in the frontal plane. The remaining six electrodes known as precordial leads lie in the transverse (horizontal) plane. The six precardial leads are unipolar and they are denoted by lead V1, V2, V3, V4, V5, and V6. All 12-leads represent twelve views of resultant vector of the heart as depicted in Fig. 1.3.

1.4 Noise in the ECG Signal

The recorded ECG signal is contaminated by various types of noise and artifacts such as 50/60 Hz noise from power line interference, baseline drift, electromyogram (EMG) noise, motion artifacts, and electrode contact noise [15]. The characteristics of several types of noises are as follows:

Power line interference: Power supply of recording ECG machine relates to line frequency, such as 50 or 60 Hz. This line frequency induces noise in recorded ECG signals. According to power line frequency (50 or 60 Hz), the ECG signal's amplitude is varied, up-to 50% of full scale deflection (peak-to-peak ECG amplitude).

Baseline wander : It is a low frequency activity in the ECG signal which is mostly from breathing with an amplitude of about 15% of peak-to-peak ECG amplitude and lies between 0.15 to 0.3 Hz.

Electromyogram (EMG) noise: It is due to muscle contraction activity, and in this, an artifactual millivolt-level potential is generated. Its typical parameters are: frequency content-DC to 10 kHz, and duration up-to 50 ms.

Motion artifacts: The slow movement of the electrode on body surface causes a change in voltage; it is due to vibration of the muscles of a patient's body. The amplitude and duration of motion artifacts are variable such as duration from 100 to 500 ms, and amplitude up-to 500% of peak-to-peak ECG amplitude.

Electrode contact noise: it is due to loss of contact between the electrode and the patient body surface. The loss of contact of electrode and body surface can be of short time duration or permanent, depending on body movements and vibrations. This is like a sudden switching action of recording of ECG. Therefore, duration of approximately one second may be skipped in maximum recorder outputs.

1.5 The Heart Disease

The heart disease describes the stage of heart that is in an abnormal condition. In the abnormal conditions heart suffers from coronary disease and heart rhythm problem. The heart disease is discovered by recording ECG signals, Echocardiography, Treadmill stress test, Cardiac catheterization, Cardiac magnetic resonance imagery (MRI), Cardiac computerized tomography (CT) scans, and pathological testing. The ECG is a non-invasive test and measure electrical impulses on body surface and reports changes in electrical

activity of heart and provides clinical information. In this thesis study, using ECG signal analysis, classification of heart diseases such as myocardial infarction, bundle branch block and Myocarditis is done. A brief description of these diseases is presented below:

Myocardial Infarction: The heart muscle cells require regular blood supply for keeping them active and working through two coronary arteries. If arteries or sub-branches are blocked and blood supply is disturbed, then heart suffers from ischemia and after prolonged obstruction of blood supply, heart cells die and the condition is known as myocardial infarction (MI). The ECG testing provides information of ischemia or MI, if the patient has angina [14].

Cardiomyopathy: It is aspecial form of heart disease that reduces pumping ability of the heart and reduces blood flow. It is due to alterations in the heart muscles such as muscles becoming enlarged, rigid or thick. The heart becomes weak and people suffer from breathlessness when they are active or sometimes when they are at rest. These situations lead to irregular heartbeats or heart attack. Types of Cardiomyopathy (CM) are: dilated Cardiomyopathy, hypertrophic Cardiomyopathy, and restrictive Cardiomyopathy. The ECG provides prelim information of Cardiomyopathy if the patient exhibits symptoms of Cardiomyopathy [14].

Bundle branch block: In the heart sometimes bundle branch gets injured which may stop the conduction of electrical impulses. The electrical impulse cannot pass through the preferred pathway across the bundle branch, it may go through muscle fibers in a fashion that both slow down the electrical movement and changes the directional propagation of the impetus. As a consequence, there is a loss of ventricular synchrony, ventricular depolarization is prolonged and there may be a corresponding fall in cardiac output [16]. The type of bundle branch blocks depends on the emplacement of the shortcoming, which starts to bundle branch blocks (BBB) such as a right bundle branch block, left bundle branch block or complete both bundle branch block. The bundle branch block can be detected by taking ECG of a patient and measuring QRS complexes in different leads.

1.6 Motivation

The heart is the most important organ of the human body which pumps blood in the circulatory system through blood vessels. The cardiologist and physician defined rules and definitions for visual ECG analysis may have subjectivity and are not uniform, so computer based interpretation is the need of this day. The task of the present work is to do ECG analysis using simple approaches and then improve diagnostic performance with available standard ECG databases such as CSE (Common Standards for Quantitative Electrocardiography), MIT-BIH (Massachusetts Institute of Technology/Beth Israel Hospital) Arrhythmia, European ST-T database and QT database, St.-Petersburg Institute of Cardiological Technics 12-lead Arrhythmia Database and PTB (Physikalisch-Technische

Bundesanstalt) database. In this thesis, we propose a simple new method for QRS detection using minimum preprocessing steps and simple decision rules, so there is no requirement of derivative, digital, band pass filter and no search back. This method is founded on the sixth power of ECG signal that intensifies the signal strength more as compared to noise and artifacts including P and T-waves. In this proposed method the signal is preprocessed by two stage median filter for removing baseline wanderThis method does not require any training, settings and estimation of model parameters. There is no requirement of filter to remove P and T-waves. This method is based on vertically differential change in slope rate by taking higher order multiplication of sample by sample in ECG signals. The average value of higher power signal is changed and attained some threshold level to discriminate amplitude of QRS complex from artifacts and, P and T-wave. In this method, the increment in the vitality of the QRS complex is much more as compared to noise artifacts or P and T waves. Now decision rules are employed to obtain high peak in QRS region, which is R or S location. This method is simple in computation, efficient and detects QRS in normal and abnormal ECGs and doesn't require any arrangement for phase shifting and fringing effect reduction. Similarly multilead ECG QRS detection is performed using composite lead. In this method, all 12 leads are added and a composite lead is designed and applied for QRS detection (with same rules as in the case of single lead), which gives better results as compared to the single lead. Next, this composite lead is also used for boundaries marking. The boundaries in composite lead are clearly noticed by the observer and marked automatically by designing software and clinical parameters are obtained which are used for interpretation and classifications.

1.7 Scope of Present Work

The computer aided ECG analysis and classification in present scenario becomes necessary due to increasing population in the world. The number of heart patients increase day-by-day, and physicians or specialists are limited.The visual criteria for differentiating heart diseases are quite perplexing and highly dependent upon the cardiologist's experience. It is difficult to provide accurate interpretation and diagnosis of heart diseases without computer based ECG systems. Thus, it is necessary to produce a simple and accurate automatic ECG analysis and diagnostic system. To ameliorate the performance of ECG system, important factors have been hashed out in this thesis such as:

(1) There is a demand of detection of QRS complex using simple and accurate method.
(2) There is a need for designing a composite lead to visualize the resultant waveform of ECG to view resultant changes in the ECG. This composite lead can be used to determine ECG wave complexes such as QRS complex, P and T-wave pattern.
(3) There is a need for accurate boundaries marking and extraction of ECG parameters for more reliable effects.

(4) There is a need for monitoring of arrhythmia and ST segment measuring using a composite lead signal.

(5) There is a need of detection of myocardial infarction, Cardiomyopathy and bundle branch block, which can be done using ANN and SVM classifiers.

1.8 Objectivesof the Present Study

The primary aim of the present work is to identify wave components, draw out features and classify the heart diseases from the ECG signals with the following aims.

(A) **Evaluation of methods for safer removal of baseline wander and motion artifacts in ECG signals**

Recorded ECG signals contain noises and artifacts such as power line noise, baseline wander, motion artifacts, etc. In this work, removal of baseline wander and motion artifacts has been carried out for detection of QRS complexes as the foremost target.

(B) **Detection of the QRS complexes and ECG wave components**

In this stage the QRS complex detection of single and multilead ECG signals has been answered by nominating a novel algorithm. Detection of P and T wave has also been implemented in multilead ECG.

(C) **Boundary marking of ECG wave components and diagnostic parameter detection**

The clinical parameters in ECG signal are calculated on the basis of boundary marking of P-QRS-T complexes, so marking boundaries of ECG wave complexes required accurate and authentic method. This has been served as the next target.

(D) **Disease diagnosis and classification.**

Diagnosis and classification of ECG signal required accurate and authentic method. Here classification of Myocardial Infarction, Cardiomyopathy, and Bundle Branch Block has been executed using the extracted diagnostic parameters.

1.9 Organization of the Thesis

The work presented in this thesis is based on the evaluation of ECG analysis and heart disease classification and is represented in the form of flowchat in Fig. 1.4. Several chapters of the thesis are organized as follows:

Chapter 1 deals with the introduction of the human heart, ECG signals, lead system, and aims of the thesis.

Chapter 2 deals with the brief literature review of ECG analysis and classification.

Chapter 3 describes different ECG database details such as CSE, MIT/BIH Arrhythmia database, European ST-T Database, MIT/BIH Noise Stress Database, QT Database, St. - Petersburg Institute of Cardiological Technics 12-lead Arrhythmia Database, and Physikalisch-Technische Bundesanstalt (PTB) Database.

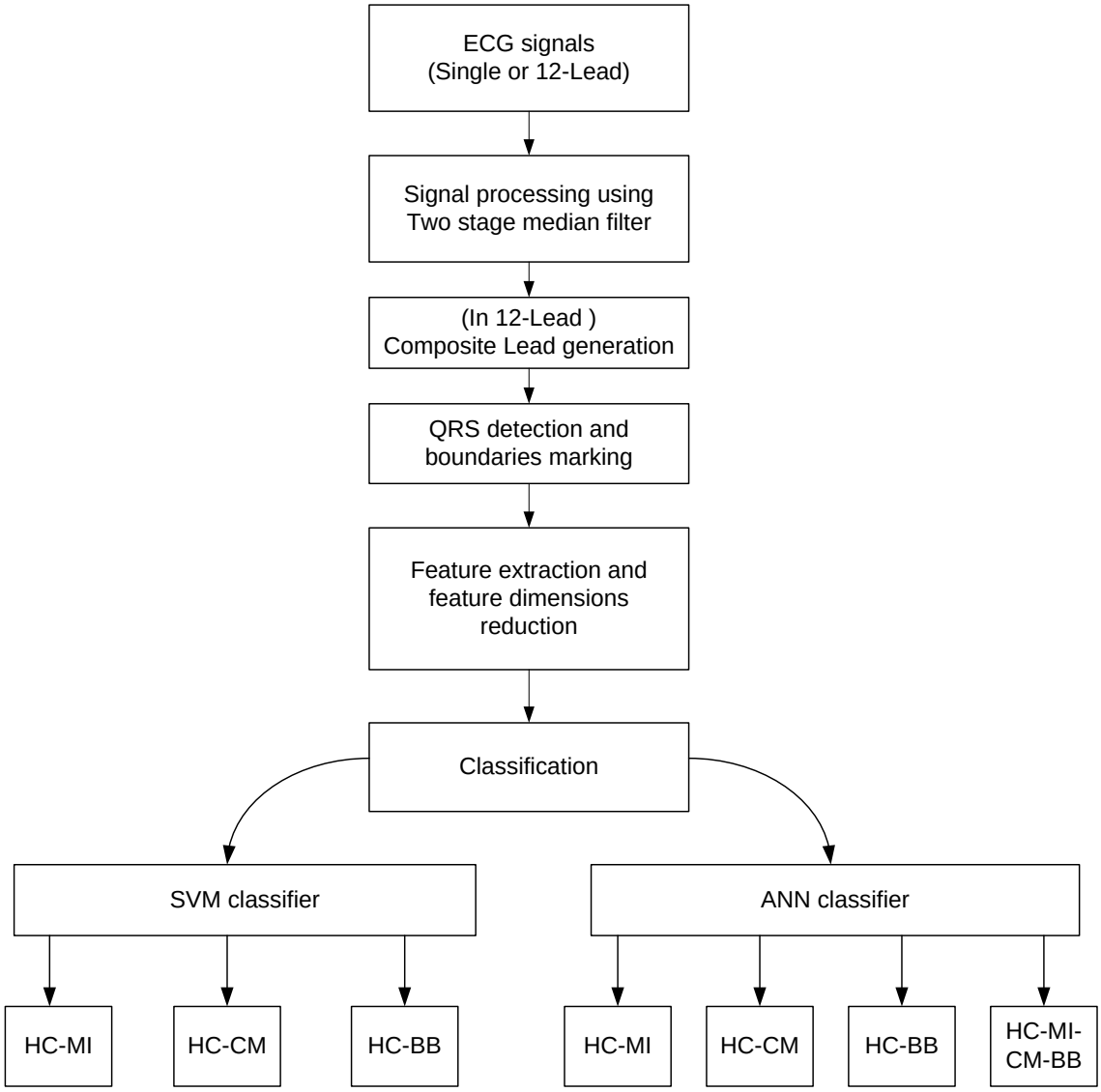

Fig. 1.4 An overall flowchart of ECG analysis and heart disease classification

Chapter 4 deals with the ECG signal processing and QRS detection. In this chapter, the procedure for single and multilead QRS detection is described and tests on various standard databases have been reported.

Chapter 5 presents boundaries marking in multilead ECG using composite lead and feature extraction for all diagnostically important parameters.

Chapter 6 presents computerized classification using SVM and ANN classifiers. In this chapter myocardial infarction detection performed using different lead arrangements, features with SVM and ANN classifiers, Cardiomyopathy and bundle branch block are depicted.

Chapter 7 describes conclusions of the work presented in this thesis, with the major work contributions and scope for future work.

In the previous chapter,general introduction of the heart anatomy, ECG lead system and heart diseases has been described. This chapter introduces a broad literature review of automatic analysis of ECG, computer programs, signal preprocessing, feature detection methods and heart disease classification using different techniques.

2.1 Overview

The computerized ECG signal analysis and interpretation, over six decades ago, started in USA by Pipberger and his group by using an orthogonal ECG lead system, and Caceres and his colleagues using 12-Lead ECG system. In the 12-Lead ECG system 10 electrodes are used to record 12 ECG waveforms from 12 different angles and is acquired continuously for monitoring for absolute 10 seconds for analysis and interpretations. The initial automatic ECG computerized programs were mostly produced by university research groups. After that development of computerized ECG programs has been shifted to industry [17]. Computers can assist a cardiologist in the task of ECG monitoring and interpretation. In the hospitals, cardiac intensive care unit (CICU), ECGs of several patients must be monitored continuously to detect life threatening abnormality that may occur. Since cardiologists are unlikely to be available to monitor the ECGs of all the patients during 24 hours, automated monitoring program to detect abnormality of heart is necessary. Over the past several years, the computerized ECG programs that provide complete 12-lead diagnostic quality ECG recording and interpretations have become common.

2.2 Computerized ECG Programs

There are various automatic ECG analysis and interpretation programs developed by researchers in the last six decades based on different approaches [17-18]. Pipberger *et al* developed AVA Program [2], Okajima *et al* developed Nagoya program [3], Bemmel *et al* developed MEANS program [4], Macfarlane *et al* developed Glasgow program [5], Rautaharju *et al* developed Dalhousie program [6], Zywietz *et al* developed Hannover program [7], Degani and Bortolan developed Padova program [8], Arnaud *et al* developed Lyon program [9], Brohet *et al* developed Louvain program [10] and Abreu-Lima and Marques de Sa' developed Porto program [11]. In addition to these, Mehta et al [19], Maheshwari et al [20], Saxena et al [21] and Mitra et al [22] have also developed programs for automatic ECG analysis and interpretation.

Pipberger et al [2] proposed Spatial velocity function for Frank lead X, Y and Z which was calculated by taking first derivatives of lead (voltage) with respect to time and then taking square root of the sum of all derivatives. This spatial velocity function was used to determine all major points. The QRS complex detection was done by utilizing the maximal spatial velocity function. The QRS location was determined as sequences of voltages which

exceed the medium maximal velocity and are followed by at least 60 ms of voltage below the median velocity. The onset and offset of QRS complexes are determined by best-fit comparisons to the templates of the spatial velocity of the hand derived wave endpoints. The Onset-offset of P-waves are determined by finding sequences of 12-16 ms of sustained spatial velocity exceeding a minimum value based on background noise level. Similarly, T-wave end point is determined by best-fit comparison to a pattern of 30 ms of positive spatial velocity followed by 20 ms with near-zero velocity. In this program three to four type diagnostic interpretationsare performed such as arrhythmia, conduction defects, and abnormality of T wave morphologies using statistical analysis. Okajima *et al* [3] proposed for recognition of fiducial point and used second order differential equation for estimating the fiducial points using four leads I, II, V1 and V6. In this method ECG signal length used is 9.6 or 24 seconds. In this method two data points with 16 ms interval are differentiated twice. The next step of the algorithm used contour classification method consisting with decision tree and perform R-ventricular hypertrophy (RVH), Left- ventricular hypertrophy (LVH), and Myocardial Infarction detection. Bemmel et al [4] proposed Modular ECG Analysis System (MEANS) using the spatial velocity function for ECGs and VCGs of the multilead CSE database. In this method lead selection purpose is spatial information of cardiac events for detection and typification. Only the P-QRS-T complexes of the four dependent leads (II, aVF, V2 and V6) are computed. In this algorithm QRS and P- wave detection and QRS typification procedure all work on signals that are in sampling rate reduced to 100 Hz. The QRS detection of MEANS is basically an off-line procedure. In case of on-line QRS detection a pseudo spatial velocity is computed from the quasi-orthogonal leads by taking the sum of the absolute values of the differentiated 100 Hz signals. This program was intended to be applied for clinic use and population screening. The MEANS used conventional criteria as well as Minnesota code for classification. Macfarlane et al [5] proposed Glasgow program for analysis of ECG which uses spatial velocity function for Frank lead and 12 Lead ECG record.In this method, the spatial velocity function is computed and determined at approximate location of all the QRS complexes. After that, QRS typing is performed according to their morphology. In this method normal sequence beat is selected to be used for averaging procedure. All beat in the same class are selected so as to have 12 beats, one from each lead. After that from these 12 averages beats, a single combined function is formed and provisional onset and termination are determined. The provisional onset and offset are then used to search for QRS onset and offset within each individual lead. Within the QRS complex the amplitude and duration of various waves, such as Q, R, and S are measured. ST segment, P and T waves are also determined. In this method interpretation of ECG was performed using P-QRS-T morphology. Rautaharju et al [6] designed Dalhousie Program for epidemiologic studies, health surveys and clinical trials. In this method, selective

averaging is used to determine average P-QRS-T cycle as output foe each set of simultaneously recoded ECG lead. This program was designed particularly for research applications and classification was performed by using Minnesota code.Zywietz et al [7] designed Hannover program for measurement and interpretation of resting and exercise ECGs. In the analysis part,the averaging strategy was used and calculation of spatial velocity function for Frank lead X, Y and Z or 12 lead ECG was done. The determination of onset-offset of P QRS and T offset is performed for the average beats of all templates. This program used hybrid model with decision trees and scoring schemes, and with multivariate probabilistic tests for classification. Degani and Bortolan [8] developed Padova program to use spatial velocity functions for ECG morphology recognition and measurement evaluation and classification was performed by fuzzy-set methodologies. Arnaud et al [9] developed a Lyon program, for diagnosis of the spatial QRS-T contour of VCGs. In this program heuristic type diagnostic strategy is used for each diagnosis. The Lyon system classifies diagnoses according to the number of non-satisfied criteria. Brohet et al [10] developed Louvain program for analysis and interpretation of Franck Orthogonal Electrocardiograms and Vector cardiograms (VCGs). This software performed the analysis of VCG to increase the clinical utility of ECG analysis. Spatial velocity function and template matching method with a mixture of threshold crossing was used for wave recognition. In this program heuristic approach was used for disease diagnosis. This program showed, on the average, satisfactory results, with a rather accurate delineation of the QRS complex and a larger variance for the P and T waves, and also, this program showed a good stability against noise. This program obtained satisfactory results in the detection of most common cardiac arrhythmias. Abreu-Lima and Marques de Sa' [11] developed a Porto program for ECG analysis and interpretation. This program runs on a microcomputer and employs the three-lead Frank VCG and detection of QRS complexes is based on double threshold methods for the spatial velocity, amplitude and its time derivative. The fiducial points of all the ECG wave components are determined by exhaustive sequential search algorithms and the diagnostic part of the program uses decision-tree logic. The diagnostic accuracy reported 76% for four classes (normal, left and right ventricular hypertrophies and myocardial infarction).

Mehta et al [19] developed computer aided program for ECG analysis and interpretation. The program stages are preprocessing, feature extraction, parameter measurement, frontal plane axis calculation and diagnostics. In this program author reported QRS detection up to accuracy 99.83%, P and T wave detection accuracy up to 96%, and delineation of peaks with boundary marking up to 99.98% and point scoring scheme was used for left and right ventricular hypertrophy detection. Maheshwari et al [20] developed computer based multilead ECG analysis and interpretation. The ECG analysis part used spatial velocity function to detect QRS complexes and then P and T waves and more than

90% of fiducial location of various waves (onset and offset of P, QRS and offset of T wave) used all leads for QRS detection and fiducial location of ECG wave components applying spatial velocity achieved 90%. In this method diagnostic interpretation of IMI, AMI, LYH, RYH and Normal ECGs of CSE multilead database have been successfully done using a heuristic approach with the agreement of local medical experts. Saxena et al [21] designed a computer program for multilead ECG analysis with modified, combined wavelet transform using single lead ECG. In this program two wavelets are used, first quadratic spline wavelet (QSWT) for QRS detection and second Daubechies six coefficients (DU-6) wavelet for P and T wave detection. The computer program has been tested on a CSE DS-3 database and an MIT/BIH database for QRS detection and detection of P & T wave has also been carried out in 125 cases of CSE DS-3.The detection sensitivity of QRS complexes is 100% using the CSE DS-3 (artificial data) and 99.90% using the MIT/BIH database. In this program an overall accuracy of 90.25% is achieved for five waves fiducial. The development software used point scoring system for diagnosis of cardiac diseases such as tachycardia, bradycardia, left ventricular hypertrophy, and right ventricular hypertrophy detection. Mitra et al [22] developed a rough-set based inference engine for ECG classification. In this method ECG features are detected in time domain and then applied rule-based rough-set decision system classifies heart disease such as normal, ischemia and myocardial infarction.

In the above paragraphs available developed programs of ECG analysis and interpretation are briefly discussed. These programs for analyzing ECG/VCG, generally used spatial velocity function and interpretation performed by heuristic or statistical approach. Pipberger et al reported that an automated ECG diagnosis could be no better than the accuracy of the waveform detection that provides its measurement values. Okajima et al reported that the automated ECG program still makes, many mistakes in boundary making or contour classification which is agreed upon unanimously. The modular ECG analysis system (MEANS) consists of modules for signal analysis and diagnostic classification. All modules underwent many changes as a function of experience, insight, and continually changing information technology. Macfarlane has also reported that there will be continuous enhancement of the system if more ECGs are interpreted on a particular system. The success of the reported techniques for processing ECG signals was demonstrated mostly through their processing on single lead or using the ECGs which do not belong to a standard database. Although the diagnostic accuracy of computer programs is tending to reach a plateau, thus there is no doubt that many years hence, it will still be possible to report on recent developments in the programs. In all programs, there is every possibility that the work will always be enhanced, modifications for improvements be made and the use of new techniques will be made for better results. The revisions and modifications of the programs are continuously in progress.

The computerized ECG program basically consists of two parts: one measurement part and another classification part. In the measurement part ECG signal is analyzed such as detection of different waves, boundaries, and set of measurements is calculated to contain all necessary information for classification. The classification part of the computerized ECG program, a diagnostic interpretation is performed on the basis of features separation in particular groups by using strategies. The literature survey of computerized ECG signal processing, analysis and classificationis discussed in detail in the next section.

2.3 ECG Signal Analysis

The signal analysis in ECG interpretation is the second stage, which consist of the steps of data acquisition, data transformation, and feature selection. In ECG signal analysis, the data transformation stage is divided into different steps such as filtering and detection, typing and dominant beat selection, and waveform recognition. In ECG signal analysis, detection of the various waveforms is done after applying the proper filtering with some suitable detection function. In sixties - seventies, many detection functions have been performed for VCG/ECG analysis [23]. There are several methods, some of which perform detection of ECG wave segments, such as P, QRS and T, while others perform detection of the QRS complexes. In the ECG analysis QRS detection is an important feature and on the basis of its accurate detection other features and parameters of the ECG signals are determined. A decent amount of research work has been done during the last six decades for the detection of QRS complex for single and multilead in the ECG signals.

2.3.1 ECG signal processing

In general, for ECG analysis QRS detection is an important task. The QRS detection is mainly divided into two parts: first part is noise removal, and the second part is QRS detection. Initially recorded ECG signal contains noise and artifacts. The ECG signal processing is necessary for analysis and classification of diseases. The best performance of an ECG processing system can be achieved, if the input data are free from noise. Artifacts in ECG can arise from different sources in a recording or monitoring system. During recording, the signal gets contaminated by the noise such as power line interference, wander baseline and other noises discussed in details in chapter 1, section 1.4. Their removal is important not only for computer processing, but also for visual examination of ECG waveform. There are many researches which developed noise reduction in the ECG signals specifically power line interference and wander baseline. There are various filters that are used for signal processing before ECG analysis, such as adaptive notch filter [24-25], digital filter [26-27], wavelet based filter [28], adaptive filter [29-31], threshold based [32], subtraction procedure method [33],median filter [34], mean-median filter [35], independent component analysis method [36], higher order statistics method [37-38].

Dragošević and Stanković [25] presented an adaptive notch filter based on recursive prediction error and obtained results were highly efficient in practice. Levkov et al [34] reported removal of power-line interference from the ECG signal, and modificationsof the subtraction method have been used in the ECG signal successfully. Yunfeng, and Rangayyan [30] developed unbiased linear adaptive filter with the normalized coefficients for the removal of noise in ECG signals. It is a popular method for filtering ECG which denoises signal with overlapping spectra. Okada [27] developed a five step digital filter, which removes components other than those of QRS complex from the recorded ECG. The final step of the filter produces a square wave and its on-intervals correspond to the segments with QRS complexes in the original signal. Ahlstrom and Tompkins [26] developed digital filters for real time ECG signal processing based on microprocessors. These filters obtained real time speeds by requiring only arithmetic. Sahambi et al [28] developed signal processing technique based on wavelet that used in ECG processing and performedsuccessfulmeasurement of QRS width in the presence of wanderingbaseline and power line interference. Poornchandra [39] developed wavelet-based denoising using subband adaptive technique for ECG signal, and perform better results than existing threshold methods. Yin et al [34] reported weighted median (WM) filter that belong to the class of nonlinear filters called stack filters, and WM filters capable of noise attenuation.

2.3.2 Feature extraction

In the computerized ECG analysis, the clinical measurement part determines the location and reference boundaries of QRS complex, P-wave, and T-wave. Mostly, ECG analysis is based on single lead and multilead signals. In a single lead ECG analysis generally lead II is preferred. In case of multilead ECG analysis, 12 lead at a time (Programs: Marquette, Glasgow and Padova), 6 leads (lead I to aVF and lead V1 toV6) at a time in program Hannover, 3 leads (II, V2 and V6) at a time in Modular program and 15 leads (12 lead ECG and 3 XYZ leads) at a time in Halifax program are used. Some programs (HP, IBM, NAGOYA and Telemed) select groups of leads at a time, such as lead group I-III, aVR-aVF, V1-V3, V4-V6 [40].

In QRS detection major problems are arising due to morphological variations of P-QRS-T waveforms, position of waveforms and the change in cyclic intervals of the ECG waveforms of different patients and noises occurrence at acquiring data [15,41]. There are many single lead QRS detection and feature extraction methods developed by researchers in the previous decades based on above criteria using different approaches [42]. These are derivatives [43-44], digital filters [45-47], filter banks [48], wavelet-transform [21,49-54], neural networks [55], support vector machine (SVM) [56], k-means [57], mathematical morphology [58-59], combined threshold method [60], moving averaging method [61], phase

space method [62], Hilbert Transform method [63-64], Body sensor network based [65], empirical mode decomposition (EMD) [66] and first-order Gaussian differentiator [67-68].

Friesen et al [15] evaluated nine different QRS detection algorithms for noise sensitivity. The noise was electromyographic interference, 60 Hz power interference, baseline drift due to respiration, abrupt baseline shift, and a composite noise constructed from all other types of noises. None of the algorithms were able to detect all QRS complexes without any false positives with all types of noises at the highest level. Thakor et al [69] carried out power spectral analysis of ECG waveform, as well as of isolated QRS complexes and episodes of noise and artifacts. A band pass filter has been used to maximize the signal (QRS) to noise (T-wave, 60 Hz, EMG etc.) ratio to detect the QRS complex. Due to the inherent variability of ECG from different persons, as well as variability due to noise and artifacts, the filter design is suboptimal in specific solutions. Pan and Tompkins [45] have developed a real-time algorithm for detection of QRS complexes of ECG signals. It reliably recognizes QRS complexes based upon digital filters and analysis of slope, amplitude, and width. Hamilton and Tompkins [46] have investigated the quantitative effects of a number of common elements of QRS detection rules using the MIT/BIH arrhythmia database. Then they developed a progressively more complex decision process for QRS detection by adding new detection rules and optimized decision rule process. Chen et al [61] developed QRS detector based on moving average computing method and obtained QRS detection rate of 99.5% using MIT-BIH Arrhythmia Database. Christov [70] developed three algorithms for QRS detection based on Adaptive Thresholding using AHA database and obtained true detection 1,64,942 for method 1, 1,65,204 for method 2, and 1,65,273 for method 3 out of 1,65,641. Escalona et al [71] developed a QRS complex alignment technique which is based on the accurate detection of a single fiducial point in the band pass filtered QRS segment. Ruha et al [72] developed QRS detector based on optimized prefiltering in conjunction with matched filter and dual edge threshold detection. In this method author obtained QRS detection error rate (ER) of 0.1 and 2.2% with records 103 and 105 respectively from MIT/BIH Arrhythmia database. Naima and Saxena [73-74] have developed two new approaches for feature extraction of the ECG signal analysis. The first method is based on mixed mathematical functions and the second one on spline functions. This method also identifies and separates P, Q, R, S, and T segments. Sornmo et al [59] have developed the mathematical model for the occurrence of pulse shaped waveforms corrupted with colored Gaussian noise. The number of waveforms, the arrival times, amplitudes and widths are regulated as unknown variables. Adaptivity of detector is gained by utilizing past as well as future properties of the signal in determining thresholds for QRS acceptance. Shaw and Savard [75] reported that the detection of subtle beat-to-beat variations in the morphology of the ECG are complicated by the effects of alignment errors and respiration. This method directly estimats the

alignment error from an ECG, derived by relating the variance to the squared slope of the averaged QRS complex. Author reported that, it was the effects of respiration that could be reduced by normalizing the amplitude of QRS complexes. Vijaya et al [55] developed QRS complexes detection based on artificial neural network (ANN) and it works on a high prediction error to indicate the occurrence of QRS complexes. Xue et al [76] have developed a QRS detector based on adaptive matched filter using artificial neural network. They obtaineda detection rate for a very noisy patient record (record number105) in MIT/BIH arrhythmia database equal to 99.5%. Sahambi et al [49] developed QRS detection and characteristic point detection using the modulus maxima of the wavelet transform using multiresolution analysis. Li et al [77] reported QRS detection based on a multiscale feature of wavelet transform. Kadambe et al [78] reported QRS detector based on the dyadic wavelet transform which is robust to time-varying QRS complex morphology and noise. Saxena et al [21] reported QRS detection using new wavelets. The new wavelet coefficients in this work have been used for QRS and feature detection with each lead. The algorithm has been tested on a CSE DS-3 database and an MIT/BIH database for QRS detection and detection of P & T wave has been also carried out in 125 cases of CSE DS-3. The detection sensitivity of QRS complexes is 100% using the CSE DS-3 (artificial data) and 99.90% using the MIT/BIH database. In this program an overall accuracy of five waves fiducial is about 90.25%. Pachori et al [66] developed a method for analysis of normal and diabetic subjects related to heart problems. In this method empirical mode decomposition is used to discriminate between diabetic and normal RR interval signals.

In the past few decades, increasing application requires multilead monitoring for telemetry and ambulatory electrocardiography. There are reliable advantages of multilead monitoring for the detection and ambulatory electrocardiography. There are reliable advantages of multilead monitoring for the detection and positioning of acute ischemia in patients with coronary artery disease. These techniques are also important for the detection and accurate diagnosis of arrhythmias, because multilead ECG recordings provide important information of P wave, QRS complex morphology and T wave that cannot be determined from two or three lead recordings. These results in a measurable change in potential difference on the body surface of the subject. A Multilead ECG system for detection and analysis uses different approaches to the multilead QRS detection based on various concepts [20,79-82].

Kors et al [79] proposed Modular analysis, ECG analysis System (MEANS) using the spatial velocity function for ECGs and VCGs in the multilead CSE database. The performance of this method for different lead configurationis (i) 11,369 beat CSE 3 simultaneous ECG lead used and find R peak 99.6%. (ii) 2847 beats CSE 3 simultaneous VCG lead used and find R peak 99.9%. (III) 2,889 beats CSE 3 simultaneous multi-lead

used and finds R peak 100%. Gritzali [83] proposed two methods for single lead and multilead QRS detection based on length transformation and energy transformation. The author that the reported QRS detection rate using CSE data set-1 for the length transformation of single and multichannel (i.e. 3-Lead) and energy transformation for multichannel are 90.66%, 99.87% and 99.13% respectively. Kyrkos et al [80] developed QRS detection for both three-Lead and single-Lead ECG signals using time recursive prediction techniques. Author reported a QRS detection accuracy of 99.00% with the CSE data set-1. Laguna et al [81] proposed multilead QRS detector on the basis of single-lead QRS detector [45], applying a multilead (15-lead) QRS detection rule considering QRS in each lead whose position do not differ by more than 90 milliseconds from one lead to another and author reported wave boundaries in multilead ECG signals within range. The researchers performed multilead QRS detection using a differentiated and low pass filtered ECG signal with wave boundaries marking in each lead in all beats. In this method onsets and offsets of P, QRS and endpoint of T waves are determined. Maheshwari et al [20] reported spatial velocity approach for detection of the QRS complexes and then another component of waves which being more than 90% of the multilead CSE data set-3. Mehta and Lingayat [56] proposed the detection of QRS complexes in 12-Lead ECG using SVM and reported a QRS detection rate of 99.97% using CSE data set-3 (MO1_001 to MO1_125). Chritov and Simova [84] developed an automatic method for Q wave onset and end of T wave using standard PTB database and QT interval (Mean ± SD) 0.83 ±16.67. Mehta et al [56,82] reported single lead based and 12 lead based QRS detection with the SVM classifier using CSE data set-3 and QRS detection sensitivity 98.86 % for single lead & 99.75 % for 12 lead ECG is obtained. Sahambi et al [85-86] in 1998 and 2000 proposed ST segment analysis and QT interval analysis using wavelet transform. Jha and Kolekar [87] reported ECG data compression and transmission for telemedicine. In this method feature extracted using discrete wavelet transform and performance of method better and comparable to other methods.

2.4 Classification

Basically, computerized ECG classification is the analysis based on the features of the ECG signals to classify one or more diagnostic categories. The disease classification being performed is based on single lead or multilead ECG analysis. The single lead ECG disease diagnosis is based on rhythm, and the rhythm is calculated by detection of QRS events. The variation in rhythm related diseases are different type of arrhythmias like tachycardia, bradycardia. The heart diseases are analyzed by some morphological measurements and it is R-R interval based [66, 88]. The single lead is mostly, used for heart rate variability (HRV). The HRV analysis is mostly used in the Incentive Care Unit (ICU) and Coronary Care Unit (CCU). Hence, HRV analysis is an attractive source of information [89, 95]. In the multilead ECG analysis, classification based on feature extraction of used multilead signals depends

on the lead selection. Several methods used for diagnostic classification of the ECG can be discerned as a heuristic [2, 4-6, 8-11], statistical [9-10, 17], KNN [96], SVM [97-103], ANN [92, 104-107], fuzzy and Neuro-fuzzy systems [104], Hidden Markov Method (HMM) [108-110], and Linear Discriminant Analysis (LDA) [103, 111], rough-set based [22], wavelet transform based [112].

Maglaveras et al [113] reported ANN has been used in the past as pattern recognition and classification with non-linear transformation. Murthy et al [114] reported homomorphic analysis and modeling of ECG signals. In this model the pole-zero pattern reveal clues to the classification of normal and abnormal signals. Silipo et al [106] developed ANN classifier for detection of arrhythmia, ischemia, and chronic diseases. In this method author used standard MIT/BIH arrhythmia data, ST-T European Society of Cardiology data, and CSE disease data. Prasad et al [115] proposed classification of arrhythmias using multi-resolution analysis with neural network. Gurgen [116] study in medical diagnosis applying neural network approach for creating diagnostic rules, the author found that when trained with sufficient data, then the NN approach was found to we superior to the statistical methods.

The researchers have developed various methods for MI detection using different lead groups and suitable features with different classifiers. Mitra et al [22] developed a rough-set based inference engine for ECG classification. In this method detection of ECG features in time domain and then applied rule-based rough-set decision system classifies heart disease such as normal, ischemia and myocardial infarction. Sharma *et al* [117] Proposed MI detection technique using multiscale energy and Eigen space features of 72 dimensional vectors of 12-Lead ECG with SVM and KNN classifiers and after reduction feature dimension used 60 feature vector to perform MI detection sensitivity 93%, specificity 99% and accuracy 96%. Sun *et* al [118], used multiple instance learning technique for MI detection with 12 ECG leads and obtained 74 dimension feature space and applying SVM, NN & KNN classifier obtained a sensitivity of 91.43% and specificity of 79.29%. In [108], Chang *et* al used four chest lead (V1, V2, V3, and V4) with HMM and Gaussian mixture. They achieved MI detection sensitivity 85.71%, specificity 79.82% and accuracy 82.50% statistically. Haraldsson*et* al [109], proposed MI detection in the 12-lead ECG using Hermite expansions with NN and obtained ROC area 0.83 of all 12 Leads. Arif *et* al [119] used 36 features of 12-Lead ECG to detect MI with KNN and obtained sensitivity and specificity 99.97% and 99.9% respectively. Reddy *et* al [120] used the 15 features of QRS measurements of chest lead V2-V4 and apply ANN classifier and obtained MI detection accuracy 79% and specificity 97%. Zheng *et* al [121] proposed MI detection through 192 lead body surface potential maps using SVM, Naïve Bayes and Random Forest classifiers and performance of MI detection accuracies are 82.8%, 81.9% and 84.5% respectively. Heden et al [122] perform MI detection based on ANN classifier and obtained sensitivity 95%, specificity 86.30%.

Jayachandran et al [123] proposed MI detection using discrete wavelet transform and obtained class accuracy 96%.

Among all the classification techniques, ANN and SVM have received lots of attention due to their demonstrated performance. The ANN classifier approach has been employed by several investigators to characterize categorization. In addition to ANN, SVM has also emerged as a powerful tool for classification. SVMs are learning based system using statistical learning theory. The recognition ability of classifiers depends on the quality of the features used as well as, the amount of training data available to them.

2.5 Conclusion

In the literature survey of related studies of ECG signal processing, generally used tools are low pass filter, bandpass filter, digital filters, wavelet transform, adaptive notch filters for removing noise and artifacts. These filters also, remove signal information. Therefore, required filter that contains all information without removing signal part is the requirement.

The QRS detection is the most important part in the ECG analysis and classification. So, QRS detection for long data in case of single lead and multilead requiresa fast detection rate. Thus, feature detection for 12 Lead ECG should be fast and accurate.Therefore, there is a need ofcomposite lead that is equivalent to all 12 leads and performs equal or higher analysis and provides betterclassification results.

The previous chapter discussed literature review on ECG signal processing, QRS detection, feature extraction and classification. Collection of standard databases, used softwares, developed and used methodsfor achieving the objectives are briefly discussed in this chapter.

3.1 Overview

The research process requires a systematic structure and scientific proof. In this process standard databases and different operating software tools are required for development of algorithms. In this thesis work, different standard databases and softwares for development of algorithms are used to fulfil required research objectives, discussed in this chapter step by step.

3.2 Standard ECG Databases

The work performed and algorithms developed in this thesis for ECG analysis and heart disease classification has used single and multi-lead ECG databases. The ECG records have been taken from the CSE (Common Standards for Quantitative Electrocardiography), MIT-BIH (Massachusetts Institute of Technology/Beth Israel Hospital) Arrhythmia, MIT/BIH Noise Stress Database, European ST-T database and QT database, St.-Petersburg Institute of Cardiological Technics 12-lead Arrhythmia Database and PTB (Physikalisch-Technische Bundesanstalt) database libraries and an indigenous data library created by the ECG recordings in the laboratory.

3.2.1 Common Standards for Quantitative Electrocardiography (CSE) Database

The CSE database [124-125] contains three libraries; all cases have been sampled at 500 Hz for 8–10 seconds duration. These are (i) CSE Three-lead measurement library, (ii) CSE Multi-Lead Measurement libraries and (iii) CSE Diagnostic Database. The 3-Lead CSE measurement data base consists of 250 original and 310 so-called artificial ECG recordings, which have been divided into two equal sets, i.e. data set-1: 125 original (EO1_001 to EO1_125) and 125 artificial (EA1_001 to EA1_155) and data set-2: 125 original (EO2_001 to EO2_125) and 125 artificial (EA2_001 to EA2_155). The multilead measurement database is also composed of 250 original and 250 so-called artificial ECG recordings (artificial data means one good real data beat repeated up to the full length of data). This data has been split into two equal sets i. e. data set-3 and data set-4. The data set 3 consists of 125 original (MO1_001 to MO1_125) and 125 artificial (MA1_001 to MA1_125) cases and data set-4 contains 125 original (MO2_001 to MO2_125) and 125 artificial (MA2_001 to MA2_125) cases of standard CSE multilead data. The diagnostic database is known as a data set-5 and contains 1220 cases. All encoded data are stored on the CD-ROM in files with the extension

dot(.) CDD (coded). After decoding they are stored on hard disk as files with the extension dot (.) DCD (decoded).

3.2.2 Massachusetts Institute of Technology/Beth Israel Hospital (MIT/BIH) Arrhythmia Database

The MIT/BIH Arrhythmia database [126] consists of 48 records and each recording consists of two leads, one modified limb lead II and another one of the modified chest leads V1, V2, V3, V4, V5 or V6. The duration of each record is 30 minutes and sampled at 360 Hz. The MIT/BIH Arrhythmia database contains 75,052 Normal beats, 2,546 APC beats, 150 Aberrated APC beats, 16 Atrial escape beats, 193 Blocked APC beats, 7,130 PVC beats, 803 Fusion PVC beats, 472 Ventricular flutter beats, 106 Ventricular escape beats, 2 SVPC beats, 7,259 RBBB beats, 8,075 LBBB beats, 279 Junctional escape beats, 83 Junctional premature beats, 982 Pacemaker fusion beats, 7,028 Paced and 33 Unclassifiable beats and overall total approximately 1,10,159 beats. In this thesis work, MIT/BIH Arrhythmia database was used for QRS detection. The details of database are given in Table 3.1.

Table 3.1 MIT/BIH Arrhythmia Database details

Record No.	Record names	Leads names	Total beats in each record	Record No.	Record names	Leads names	Total beats in each record	Record No.	Record names	Leads names	Total beats in each record
1	100	MLII, V5	2273	17	117	MLII V2	1535	33	212	MLII V1	2748
2	101	MLII, V1	1865	18	118	MLII V1	2288	34	213	MLII V1	3251
3	102	V5, V2	2187	19	119	MLII V1	1987	35	214	MLII V1	2262
4	103	MLII, V2	2084	20	121	MLII V1	1863	36	215	MLII V1	3363
5	104	V5, V2	2229	21	122	MLII V1	2476	37	217	MLII V1	2208
6	105	MLII, V1	2572	22	123	MLII V5	1518	38	219	MLII V1	2287
7	106	MLII, V1	2027	23	124	MLII V4	1619	39	220	MLII V1	2048
8	107	MLII, V1	2137	24	200	MLII V1	2601	40	221	MLII V1	2427
9	108	MLII, V1	1774	25	201	MLII V1	2000	41	222	MLII V1	2483
10	109	MLII, V1	2532	26	202	MLII V1	2136	42	223	MLII V1	2605
11	111	MLII V1	2124	27	203	MLII V1	2980	43	228	MLII V1	2053
12	112	MLII V1	2539	28	205	MLII V1	2656	44	230	MLII V1	2256
13	113	MLII V1	1795	29	207	MLII V1	2332	45	231	MLII V1	1573
14	114	V5,MLII	1879	30	208	MLII V1	2955	46	232	MLII V1	1780
15	115	MLII V1	1953	31	209	MLII V1	3005	47	233	MLII V1	3079
16	116	MLII V1	2412	32	210	MLII V1	2650	48	234	MLII V1	2753
Overall Total beats											**110159**

3.2.3 MIT/BIH Noise Stress Database

The MIT/BIH Noise Stress database [127] contains 12 half-hour ECG recordings and 3 half-hour recordings of noise typical in ambulatory ECG recordings. The noise recordings

were made using physically active volunteers and standard ECG recorders, leads, and electrodes; the electrodes were placed on the limbs in positions in which the subjects' ECGs were not visible. The three noise records were assembled from the recordings by selecting intervals that contained predominantly baseline wander (in record ‘bw’), muscle artifact (in record ‘ma’), and electrode motion artifact (in record ‘em’). The Electrode motion artifact is generally considered the most troublesome, since it can mimic the appearance of ectopic beats and cannot be removed easily by simple filters, as can noise of other types. The ECG recordings were created by the script nstdbgen- using two clean recordings (118 and 119) from the MIT-BIH Arrhythmia Database, to which calibrated amounts of noise from record 'em' were added using nst. The process of making such records is now simpler; the simplified script nstdbgen can be used with current versions of the WFDB software package to recreate these records. Noise was added beginning after the first 5 minutes of each record, during two-minute segments alternating with two-minute clean segments. The signal-to-noise ratios (SNRs) during the noisy segments of these records are depicted in Table 3.2.

Table 3.2 MIT/BIH Noise Stress Database details

Records	**SNR (dB)**	**Total beats in each case**	**Records**	**SNR (dB)**	**Total beats in each case**
118e24	24	2278	119e24	24	1987
118e18	18	2278	119e18	18	1987
118e12	12	2278	119e12	12	1987
118e06	06	2278	119e06	06	1987
118e00	00	2278	119e00	00	1987
118e_6	-6	2278	119e_6	-6	1987
Total		**13668**	**Total**		**11922**

3.2.4 European ST-T Database

The European ST-T Database [128] contains each two hours, two channel worth of ambulatory ECG recordings, and annotated beat-by-beat. This database consists of 90 annotated excerpts of ambulatory ECG recordings. The duration of each record is 120 minutes and sampled at 250 Hz. This database contains approximately normal beats 7,84,633; premature ventricular contraction (PVC) beats 44,677**,** Supraventricular premature or ectopic beat (SVPB) 1093**,** Unclassifiable beat (Q) 11, Fusion of ventricular and normal beat (F) 1 and overall approximate 7,90,559 beat labels. The details of database are given in Table 3.3.

Table 3.3 European ST-T database details

Record No.	Record names	Leads names	Total beats in each record	Record No.	Record names	Leads names	Total beats in each record	Record No.	Record names	Leads names	Total beats in each record
1	e0103	V4,MLIII	7296	31	e0155	MLIII, V4	8125	61	e0411	V5, MLI	9934
2	e0104	MLII,V4	7696	32	e0159	MLIII, V4	9196	62	e0413	V2, V5	8149
3	e0105	MLIII,V4	6629	33	e0161	V4,MLIII	8858	63	e0415	V2, V5	11407
4	e0106	MLIII,V3	7152	34	e0162	MLIII, V4	10616	64	e0417	V5,MLI	9253
5	e0107	D3, V4	7029	35	e0163	MLIII, V4	7616	65	e0418	V5,MLI	11706
6	e0108	V4, MLIII	6597	36	e0166	V4, MLIII	6399	66	e0501	V2,V5	7758
7	e0110	V3, MLIII	6971	37	e0170	V4, MLIII	8824	67	e0509	V2,V4	8091
8	e0111	MLIII,V4	7535	38	e0202	V5, MLI	9855	68	e0515	V2,V5	10694
9	e0112	MLIII,V4	5506	39	e0203	V5, MLI	10165	69	e0601	V5,MLIII	8769
10	e0113	MLIII, V4	8946	40	e0204	V5, MLI	11472	70	e0602	V5,MLIII	11128
11	e0114	MLIII,V4	5543	41	e0205	V5, MLI	11807	71	e0603	V5,V2	7930
12	e0115	V5, MLII	11313	42	e0206	V5, MLI	10916	72	e0604	V2,MLIII	7815
13	e0116	V4, MLIII	4494	43	e0207	V5, MLI	7197	73	e0605	V5,MLIII	11386
14	e0118	V4, MLIII	7080	44	e0208	V5, MLI	8695	74	e0606	V5,MLIII	9624
15	e0118	MLLII, V4	7718	45	e0210	V5, MLI	8739	75	e0607	V5,V4	10266
16	e0121	V4, MLIII	10629	46	e0211	V5, MLI	14970	76	e0609	V5,MLIII	9321
17	e0122	V4, MLIII	11363	47	e0212	V5, MLI	10829	77	e0610	V5,MLIII	7999
18	e0123	V4, MLIII	9175	48	e0213	V5, MLI	11070	78	e0611	V5,MLIII	5812
19	e0124	V4, MLIII	9213	49	e0302	V3, V5	10340	79	e0612	V5,MLIII	6887
20	e0125	V4, MLIII	9066	50	e0303	V2 V5	8874	80	e0613	V5,MLIII	7726
21	e0126	V4, MLIII	8291	51	e0304	V3, V5	8358	81	e0614	V5,V1	11107
22	e0127	V4, MLIII	9391	52	e0305	V2, V5	9417	82	e0615	V5,MLIII	7192
23	e0129	MLIII, V3	5568	53	e0306	V2, V5	7903	83	e0704	V5,V1	9718
24	e0133	MLIII, V3	6570	54	e0403	V5, V1	9297	84	e0801	V1,V5	9388
25	e0136	MLIII, V4	7044	55	e0404	V5, MLI	6940	85	e0808	V5,V1	11075
26	e0139	MLIII, V4	10631	56	e0405	V5, V1	11091	86	e0817	V5,V1	7554
27	e0147	MLIII, V4	6374	57	e0406	V5, MLI	8945	87	e0818	V5,V1	10129
28	e0148	MLIII, V4	6676	58	e0408	V5, MLI	9037	88	e1301	V1,V5	8740
29	e0151	V3, MLIII	7546	59	e0409	V5, MLI	12885	89	e1302	V1,V5	8350
30	e0154	MLIII, V4	6782	60	e0410	V5, MLI	7527	90	e1304	V1,V5	7864
Overall Total beats											**790559**

3.2.5 The QT Database

The QT Database contains ECGs which were selected to represent a wide variety of QRS and ST-T morphologies, in order to challenge QT detection algorithms with real-word variability [129]. The records were selected primarily from among existing ECG databases, including MIT-BIH Arrhythmia Database, the European Society of Cardiology ST-T Database, and several other ECG databases collected at Boston's Beth Israel Deaconess

Medical Center. The QT database contains 105 cases sampled at 250 Hz. This database contains approximately 87,679 beat labels as depicted in Table 3.4.

Table 3.4 QT Database details

Record No.	Record names	Total beats in each record	Record No.	Record names	Total beats in each record	Record No.	Record names	Total beats in each record
1	sel100	1135	36	sel16272	851	71	sele0603	870
2	sel102	1088	37	sel16273	1112	72	sele0604	1031
3	sel103	1048	38	sel16420	1063	73	sele0606	1442
4	sel104	1109	39	sel16483	1087	74	sele0607	1184
5	sel114	862	40	sel16539	922	75	sele0609	1127
6	sel116	1185	41	sel16773	1008	76	sele0612	751
7	sel117	766	42	sel16786	925	77	sele0704	1094
8	sel123	756	43	sel16795	761	78	sel30	30
9	sel213	1642	44	sel17453	1047	79	sel31	30
10	sel221	1247	45	sele0104	804	80	sel32	30
11	sel223	1302	46	sele0106	896	81	sel33	30
12	sel230	1077	47	sele0107	812	82	sel34	30
13	sel231	732	48	sele0110	871	83	sel35	31
14	sel232	865	49	sele0111	907	84	sel36	31
15	sel233	1533	50	sele0112	684	85	sel37	50
16	sel301	1351	51	sele0114	699	86	sel38	30
17	sel302	1500	52	sele0116	558	87	sel39	30
18	sel306	1040	53	sele0121	1436	88	sel40	30
19	sel307	853	54	sele0122	1415	89	sel41	30
20	sel308	1282	55	sele0124	1121	90	sel42	30
21	sel310	2012	56	sele0126	945	91	sel43	30
22	sel803	1026	57	sele0129	670	92	sel44	30
23	sel808	903	58	sele0133	840	93	sel45	30
24	sel811	704	59	sele0136	809	94	sel46	30
25	sel820	1159	60	sele0166	813	95	sel47	30
26	sel821	1555	61	sele0170	897	96	sel48	30
27	sel840	1180	62	sele0203	1246	97	sel49	30
28	sel847	801	63	sele0210	1063	98	sel50	32
29	sel853	1111	64	sele0211	1575	99	sel51	30
30	sel871	917	65	sele0303	1045	100	sel52	30
31	sel872	991	66	sele0405	1216	101	sel17152	1628
32	sel873	852	67	sele0406	959	102	sel14046	1260
33	sel883	892	68	sele0409	1737	103	sel14157	1081
34	sel891	1267	69	sele0411	1202	104	sel14172	663
35	sel16265	1031	70	sele0509	1028	105	sel15814	1036
Overall Total beats								**87679**

3.2.6 St. Petersburg 12-lead Arrhythmia Database

This database consists of 75 annotated recordings extracted from 32 Holter records. Each record is 30 minutes long and contains 12 standard leads, each sampled at 257 Hz, with gains varying from 250 to 1100 analog-to-digital converter units per milli volt. The reference annotation files contain over 1,75,000 beats annotations in all. The original records were collected from patients undergoing tests for coronary artery disease. None of the patients had pacemakers; most had ventricular ectopic beats. In selecting records to be included in the database, preference was given to subjects with ECGs consistent with ischemia, coronary artery disease, conduction abnormalities, and arrhythmias [130]. Table 3.5 depicts details of records.

Table 3.5 St. Petersburg 12-lead Arrhythmia Database

S. No.	Record names	Patient No.	Total beats in each record	S. No.	Record names	Patient No.	Total beats in each record	S. No.	Record names	Patient No.	Total beats in each record
1	I01	1	2757	26	I26	12	1509	51	I51	23	2777
2	I02	1	2674	27	I27	13	2605	52	I52	23	1747
3	I03	2	2451	28	I28	13	1717	53	I53	23	2262
4	I04	2	2423	29	I29	14	2621	54	I54	24	2363
5	I05	2	1776	30	I30	14	2462	55	I55	24	2166
6	I06	3	2493	31	I31	14	3210	56	I56	24	1705
7	I07	3	2706	32	I32	14	1619	57	I57	25	2867
8	I08	4	2131	33	I33	15	1837	58	I58	25	2325
9	I09	5	2997	34	I34	15	1965	59	I59	26	2148
10	I10	5	3682	35	I35	16	3675	60	I60	26	2475
11	I11	5	2106	36	I36	16	3911	61	I61	26	1454
12	I12	6	2809	37	I37	16	2461	62	I62	27	2269
13	I13	6	2023	38	I38	17	2699	63	I63	27	1994
14	I14	6	1866	39	I39	17	1775	64	I64	27	1913
15	I15	7	2635	40	I40	18	2666	65	I65	28	2664
16	I16	8	1522	41	I41	18	1630	66	I66	28	2340
17	I17	8	1672	42	I42	19	3109	67	I67	28	2974
18	I18	9	3084	43	I43	19	2209	68	I68	29	2644
19	I19	9	2063	44	I44	20	2494	69	I69	29	2169
20	I20	10	2652	45	I45	20	1928	70	I70	30	1666
21	I21	10	2184	46	I46	20	2658	71	I71	30	1670
22	I22	10	3126	47	I47	21	1953	72	I72	31	2269
23	I23	11	2205	48	I48	21	2357	73	I73	31	1992
24	I24	11	2571	49	I49	22	2147	74	I74	32	2404
25	I25	12	1712	50	I50	22	2998	75	I75	32	2103
Overall Total beats											**175895**

3.2.7 Physikalisch-Technische Bundesanstalt (PTB) Database

This database contains 549 records from 290 subjects. Each subject is represented by one to five records. There are no subjects numbered 124, 132, 134, or 161. Each record includes 15 simultaneously measured signals: the conventional 12 leads (I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, V6) together with the 3 Frank leads ECGs (VX, VY, VZ). Each signal is digitized at 1000 samples per second, with 16 bit resolution over a range of ± 16.384 mV. This is diagnostic data containing Healthy controls and different diseases such as Myocardial infarction, Cardiomyopathy/Heart failure, Bundle branch block, Dysrhythmia, Myocardial hypertrophy, Valvular heart disease, Myocarditis [131]. The clinical summary of PTB data subject wise is given in following Table 3.6.

Table 3.6 Different Heart Diseases PTB Database

S. No.	Diagnostic class	No. of subjects	Cases	Remarks
1	Bundle branch block	15	17	
2	Cardiomyopathy	15	17	
3	Dysrhythmia	14	16	
4	Healthy Control	52	80	
5	Heart failure	3	3	
6	Myocardial Hypertrophy	7	7	
7	Myocardial Infarction	148	368	
8	Myocarditis	4	4	
9	n/a Clinical summary not available	22	27	
10	Palpitation	1	1	Miscellaneous
11	Stable angina	2	2	Miscellaneous
12	Unstable angina	1	1	Miscellaneous
13	Valvular heart disease	6	6	
Total	13	290	549	

3.2.8 Lab recorded database

Biopac-150 was used with Fluke for candidate data recording. Different types of data, selecting proper ranges for ST elevation and depression (positive 0.8mv to negative 0.8mv). Similarly, different sinus arrhythmias data were recorded from 30BPM to 300BPM, and different PVCS such as 6, 12 and 24. Atria 6100 ECG machine was used for recording different subjects such as students, security persons, staff members and some medical shivers. All data were recorded at 500 samples per second.

3.3 Methodology

The research methodology is a thought process, which performs a structured research to understand scientifically by holding all its steps together. It represents an overview of the set paths that are needed to be followed to achieve research targets. An appropriate research steps are designed for this study to carry out the experiments, and

evaluate the performance in a proper sequence. The description of experiments carried out in the present research work mainly divided in two parts, ECG analysis and classification.

3.3.1 ECG analysis

The ECG signal analysis is an important part in computer assisted ECG diagnostic system, various steps for ECG signal analysis are briefly discussed as follows.

Preprocessing: The recorded data contains noise and artifacts such as power line interference, baseline wander, EMG and electrode contact noise. In this proposed method the signal is preprocessed by two stage median filter for removing baseline wander using sampling frequency f_s. In the first step, sliding window size $f_s/2$ is used and median values are determined and stored in an array and in the second step, window size f_s is used and median values are determined and stored in another array. Subtracting these median values from original signal gives drift free signal. In this method, only baseline wander is removed.

QRS detection: In the ECG signals, Q, R and S waves are high frequency, sharp waves whereas P and T waves are low frequency and less sharp waves. The data of Q, R and S waves are having linear slope variation. The proposed QRS detection method employs a simple two stage median filter for removing baseline drift by using two window widths related to the sampling frequency of recorded data. After that, the baseline drift free signal is further enhanced by point to point six times data multiplication where the sharp peaks such as Q, R, S are more enhanced than artifacts and P & T waves. For automatic QRS detection, a threshold value is required to distinguish between the QRS complex and other ECG wave components such as P and T waves. This threshold value is related to the amplitude of the peak value of the QRS complex. In this proposed method, mean value of enhanced signal works as threshold of separation of QRS from other waves. The above criterion is used for QRS detection in single lead and multilead ECG.

Single lead QRS detection: A simple and efficient new method for QRS detection in Electrocardiogram is proposed in this research work. The initial data is preprocessed using two stage median filter for removing baseline drift. The second stage enhances the peaks of ECG wave components by using the sixth power of a signal. The next stage identifies the QRS complex by taking a variable window size. The performance of the new algorithm is evaluated against the standard databases. The QRS detection was also performed on 12 datasetsnoisy, full lengths (118e24 to 118e_06 and 119e24 to 119_06) from MIT–BIH Noise Stress Test Database and obtained performance is higher or comparable to other algorithms in literature.

Multilead QRS detection: QRS detection in 12-Lead Electrocardiogram (ECG) using composite lead and peak enhancement method is proposed in this thesis. Initially raw signals of 12-Lead electrocardiogram having sampled frequency f_s are pre-processed for baseline wander removal using a two stage median filter with window widths of $f_s/2$ and f_s respectively.

The point by point average of the preprocessed signals corresponding to 12-Leeds is taken to generate a composite lead. In order to obtain a variable size search window for QRS detection, the composite lead is enhanced by the sixth power of the signal and its mean value is determined. The maximum value in the search space defined by the search window was mapped on the composite lead and other 12 ECG leads of 12-lead ECG individually for QRS detection. The performance of the algorithm is evaluated against CSE (Common Standards for Quantitative Electrocardiography) multilead measurement database, St. Petersburg Institute of Cardiological Technic's 12-lead Arrhythmia Database and PTB Database Boundary marking of ECG wave components and diagnostic parameter detection

Boundary marking of ECG wave components and diagnostic parameter detection: Boundary point's detection in 12-Lead ECG simultaneously recorded, using composite lead is proposed in this work. The complexes of this composite lead are better enhanced and noise free than others in any of the 12 leads. The initially raw signal is preprocessed by two stage median filters to remove baseline drift using sliding window $f_s/2$ and f_s respectively. In the second stage, the composite lead is generated by the combination of all 12-leads. The morphology of composite lead is similar to other 12-leads, but with more enhanced wave complexes and intervals with reduction of noise. The third stage enhances the complexes of composite signal by using the sixth power of this signal, using the mean value of this enhanced signal as a threshold to determine the high peak of QRS of composite signal and individual leads at variable window size. After detection of the QRS location of composite lead, QRS_{onset} and QRS_{offset} are determined by using the standard deviation method. After detection of P-wave location, P_{onset} and P_{offset} are determined by using the standard deviation method and similarly T wave location is detected and T_{end} is marked.

For automatic ECG analysis and diagnosis system a dominant beat is required for measurements and classification. Here it is proposed to determine average beat in 10 second recoded ECG signal. All beats are aligned about high peak (R or S wave) position as a center location and each beat lying in the range from P_{onset} -100 msec to T_{end}+100 msec in 2000 ms window size and then average beat of composite lead and all the leads of 12 lead ECG is determined. The onsets of P, QRS and offsets of P, QRS and T wave are detected on the composite beat (average beat) and mapped on boundary values of composite beat in all the average beats of 12-leads. After determination of P duration, QRS complex duration, ST-T complex interval and QT interval, other parameters such as peak to peak amplitude, area, mean, standard deviation, skewness and kurtosis of QRS duration and ST-T complex interval of all average beats of 12-lead ECG are calculated.

3.3.2 Feature Dimension Reduction Technique

The general problem in data processing is that large amount of data are expensive to store, transmit and process. For storing large storage space, for transmitting required to have

high bandwidth and for processing, required fast computing system to reduce the large processing time. To reduce the amount of data would mean a reduction in expenses. But simply throwing away part of the data would result in a loss of information, which could be important. In so called random data, such as signals, images and other samples, there is however a difference in how important each part of data is to the information which is stored in the data. By leaving out the part of data which is the least valuable to the information to the information, we reach a reduction of the amount of data. The main purpose of the feature space dimensionality reduction is to avoid curse of dimensionality, reduce amount of time and memory size required by data mining algorithms and achieve higher accuracy. In the present work, the principal component analysis (PCA) has been used to obtain optimal features for classification task.

Principal component analysis is a statistical method that generates a new set of variables known as principal components. Principal component analysis has been used successfully in the various field such as face recognition, image compression, EEG analysis, diagnosis of diseases of cotton leaves and as well as ECG analysis [99, 100, 103-139]. PCA is defined as orthogonal linear transformation, that transforms the data to a new coordinate system such that the first greatest variance by some projection data comes to lie in the first coordinate, the second greatest variance on the second coordinate, and so on [140-142]. In this study PCA is used for parameter dimensionality reduction and optimize the number of principal components (PCs) to perform heart disease classification.

3.3.3 Classification Method

In computerized ECG diagnosis system classification part is the second part, in which extracted features are used for classifications. In this section briefly described method for detection of myocardial infarction, cardiomyopathy and bundle branch block using SVM and ANN classifier.

3.3.3.1 Support Vector Machine based Classifier

The SVM is a most suitable technique for data classification. The classification task in this technique mostly uses separating data (numeric values) into training and testing sets by building an optimized hyper plane, using kernel functions with suitable conditions. The main aim of this classifier is to produce a model on the basis of training data, which shows the target values of the test data. In this study, we apply LibSVM for MI classification. The calculated features are applied as SVM format such as numeric values. To avoid numerical difficulties and large numerical differences in attributes, we used Min-Max method for rescaling of attributes in the range [-1, +1]. According to LibSVM guide, we considered the kernel function radial bias function (RBF) with tenfold cross-validation to find best parameter $C \varepsilon \{2^{-4}, 2^{-3}, \ldots\ldots 2^{15}\}$ and $\gamma \varepsilon \{2^{-15}, 2^{-14}, 2^{-13}, \ldots\ldots 2^{5},\}$ to train the whole training data set [97,

102, 143]. The SVM has been used successfully in the various field such as face recognition image compression, health diagnosis and other fields [144].

3.3.3.2 Artificial Neural Network based Classifier

The Artificial Neural Network (ANN) consist of simple nodes and operating in parallel. Its processing units analogous to neurons in the brain. Each node has a node function, associated with it which, along with a set of local parameters determines the output of the node, given an input. Artificial Neural Network thus is an information processing system. In this information processing system, the nodes called neurons, process the information. The signals are transmitted by means of connected links. The link possesses an associated weight, which is multiplied along with the incoming net input (signal) for any neural net. The output signal is obtained by applying activations of the net input. Thus, ANN represents the major extension to computation. The ANN performs the operation similar to the human brain. Therefore, ANN are very flexible and powerful tool in medical diagnosis and classification.

The ANN is a massively parallel distributed processor made up of simple processing units that has a natural tendency for storing experimental knowledge to design the model to perform a particular classification problem. The data regarding the categorization problem are passed around through its weights and their associations. The learning algorithm used in neural network changes the weights of the net in the manner to gain a desired design objective. Once it is successfully trained, it can give an estimated class to previously unseen pattern vector. These approximated outputs are used in the decision process to classify that pattern.The ANNshave been used successfully in the various field such as face recognition, image compression, health diagnosis and other fields [145-150].

In this work, an ANN classifier tool used various primary steps: to collect features of data, create networks, configure the network, initialize the weights and biases, training the network, validation the validation the network, and use the network (testing) for classification. To avoid numerical difficulties and large numerical differences in attributes, we used Min-Max method for rescaling of attributes in the range [-1, +1]. In the next section briefly described method for detection of myocardial infarction, cardiomyopathy and bundle branch block using SVM and ANN classifier.

3.4 Conclusion

The material and methodology described in this chapter is to accomplish the research objectives of the present work on ECG analysis and classification. In the first section, overview of standard ECG databases such as CSE, MIT/BIH arrhythmia data, MIT/BIH Noise Stress Database, European ST-T Database and QT Database, St.-Petersburg Institute of Cardiological Technics 12-lead Arrhythmia Database, PTB Database libraries and also

indigenous data library created by the ECG recording in the laboratory, is presented. Second and section briefly explains about QRS detection, boundaries marking, feature extraction, and classification are briefly discussed which are described in more detail in subsequent chapters.

CHAPTER 4: ECG SIGFNAL PROCESSING AND QRS DETECTION

In the previous chapter various types standard databases, methods developed for signal processing, QRS detection, boundary marking and classification of diseases have been discussed. In this chapter signal processing and QRS detection for both type single Lead and 12 Lead ECG signal have been discussed in detail.

4.1 Overview

The Electrocardiogram (ECG) is the most suitable technology for recording of electrical activity generated by myocardial contraction. The pattern of electrical propagation is not random, but spreads over the structure of the heart in a coordinated manner. This results in a measurable change in potential difference on the body surface of the subject. Fig. 2.1 shows the characteristic shape, segments and time intervals of ECG signals. The QRS complex is the most important waveform known as the reference waveform for analysis of ECG signals. Cardiologist or Clinician diagnoses cardiac abnormalities by observing ECG. The performance of an automatic ECG analyzing system depends mostly upon the accurate and reliable detection of the QRS complex. Once the location of The QRS complex is determined, then another wave component of ECG signal such as P & T waves, PR interval, QRS interval, QT intervals and PQ & ST segments is determined with respect to the position of the QRS complex. Therefore, detection of accurate QRS complex is the most important objective in automatic ECG signal analysis. In the present work I have developed two methods for QRS detection: (1) Single lead based QRS detection and (2) Multilead (12-lead ECG) QRS detection. Detail steps of single lead and multilead based QRS detection method are described in this chapter.

4.2 ECG Signal Processing

Various methods have been used for removing noise and artifacts in the literature discussed in chapter 2, such as notch filter, adaptive filter, band-pass filter, digital filters, wavelet based and median filter. In this work I have developed a two stage median filter to remove baseline wander using window width size *fs/2* and *fs* for stage first and second in terms of sampling frequency *(fs),* detail steps discussed in QRS detection section. Median filter is a nonlinear filter which is simple to operate with high speed.

The proposed QRS detection method employs a simple two stage median filter for removing baseline drift by using two window widths related to the sampling frequency of recorded data. So, two stage median filter is to remove baseline wander and motion artifact both belong to low frequency range. After that, the baseline drift free signal is further enhanced by point to point six times data multiplication where the sharp peaks such as Q, R, and S are more enhanced than artifacts and P&T waves. Hence other filters are not required

in the proposed QRS detection method. Detail steps of preprocessing and QRS detection are explained in the next section.

4.3 QRS Detection

In QRS detection for single lead ECG, major problems are arising due to morphological variations of P-QRS-T waveforms, position of waveforms and the change in cyclic intervals of the ECG waveforms of different patients and noises occurrence in acquiring data [15, 41]. Therefore, most of QRS detectors described in the literature [42] can be divided into two parts: the preprocessor and decision rules. There are many QRS detection methods developed by researchers in the last three decades based on above criteria using different approaches. These are derivatives [43-44], digital filters [45-47], wavelet-transform [21, 49-54], neural networks [55], support vector machine (SVM) [56], k-means [57], mathematical morphology [58], combined threshold method [60], moving average method [61, phase space method [62], Hilbert Transform method [63] and Body sensor network based method [65].

These existing derivative and digital filter based algorithms determine QRS complex assuming a noise free ECG and without P & T waves removed by using a low pass filter, high pass filter or band pass filter. Similarly, in wavelet transform a preselected frequency band is assumed in which QRS complex energies exist using a combination of low and high pass filter. In wavelet transform method QRS complex energies decrease, if the scale is larger than 2^4 and the energies of artifacts increase for scales greater than 2^5 [49]. In wavelet based methods there are no general rules for selecting a wavelet for a particular application. Selection criteria of wavelet for a particular application depend on trial method. In wavelet methods, fringing effects occur at both the ends of the signal and phase shift problems also occur. So in order to overcome these effects some operations are needed. Methods based on ANN and SVM require exhaustive training, settings and estimation of model parameters. Most of these techniques for QRS detection are computationally complex because of using more preprocessing steps.

In this work, a simple new method is proposed for QRS detection using minimum preprocessing steps and simple decision rules. There are no requirements of derivative, digital, band pass filters and no search back. This method is based on the sixth power of ECG signal that intensifies the signal strength more as compared to noise and artifacts including P and T-waves. In this proposed method the signal is preprocessed by two stage median filter for removing baseline wander using sampling frequency f_s. This method does not need any training, settings and estimation of model parameters. There is no requirement of filter to remove P and T-waves. This method is based on vertically differential change in slope rate by taking higher order multiplication of sample by sample in ECG signals. The average value of higher power signal is changed and attained some threshold level to discriminate amplitude of QRS complex from artifacts and, P & T-wave. In this method, the

increase in the energy of the QRS complex is much more as compared to noise artifacts or P and T waves. Now decision rules are applied to find high peak in QRS region, which is R or S location. This method is simple in computation, efficient and detects QRS in normal and abnormal ECGs and doesn't require any arrangement for phase shifting and fringing effect reduction. The proposed single and multilead QRS detection method has been tested on a large scale using many standard ECG databases such as CSE, MIT/BIH AD, ESC ST-T and QT, PTB database and also tested noise performance on MIT/BIH Nose Stress Database. So both method are useful for ST segment analysis, arrhythmia analysis and different heart disease analyses.

4.3.1 Methodology for QRS Detection

In general, the QRS detection is mainly divided in two parts: first part is noise removal, and second is QRS detection. Recorded ECG signal has noises such as 50/60 Hz power line interference due to power line, electromyogram noise due to muscle tremor which belongs to high frequency noise, baseline wander due to sudden patient movement or breathing and motion artifact due to bad electrode. Baseline wander and motion artifact belong to low frequency in which the baseline wander frequency is lower than 1 Hz. In this study, we considered only baseline wander as removable and QRS is detected in the presence of other noises. The various methods used for this purpose in the literature are band-pass filter [45], wavelet based [61] and median filter [34]. In this study for removing baseline wander drift, we considered two stage median filter using window widths $f_{s/2}$ and f_s. Median filter is a nonlinear filter which is simple to operate with high speed. The proposed QRS detection method employs a simple two stage median filter for removing baseline drift by using two window widths related to the sampling frequency of recorded data. After that, the baseline drift free signal is further enhanced by point to point six times data multiplication where the sharp peaks such as Q, R, S are more enhanced than artifacts and P & T waves.

In the ECG signals, Q, R and S waves are high frequency, sharp waves whereas P and T waves are low frequency and less sharp waves. The data of Q, R and S waves have linear slope variation. If squaring or higher power of the signal is done than data becomes nonlinear. In this case ratio of slope rate of sharp waves with respect to less sharp or slow waves will increase and will discriminate the QRS complex with respect to P & T waves.

For automatic QRS detection, a threshold value is required to distinguish between the QRS complex and other ECG wave components such as P and T waves. This threshold value is related to the amplitude of the peak value of the QRS complex. In this proposed method, mean value of enhanced signal works as the thresholdof separation of QRS from other waves, as shown in Fig. 4.1. In the first step, when the signal is without multiplication, the mean value of signal crosses all peaks, as shown in Fig 4.1 (a). In the second step when the signal is squared, the mean value of signal crosses all peaks, but with an upward shift

which is more than that in the first step as shown in Fig. 4.1 (b). Similarly, mean of third and fourth steps is shifted upwards, which is clearly higher than artifacts and some waves as shown in Fig. 4.1 (c) and 4.1 (d). Now in the fifth step when a power of the signal is fifth, the mean value **'a'** of the signal becomes higher than all artifacts and P and T- waves with a possibility of touching T-wave as shown in Fig. 4.1 (e). In the sixth step when a power of the signal is sixth, the mean value **'a'** of signal is clearly above all waves except QRS complex waves as shown in Fig. 4.1 (f). In this step, 'R' or 'S' wave peaks are clearly distinguished from the peaks of P & T waves. So the sixth power of the signal and mean value **'a'** has been used to detect 'R' peaks in this work. A variable window width has been selected by choosing mean value **'a'** of sixth power of the signal as a threshold to determine exact location of either 'R' or 'S' peak (on the mapping of the time window in enhanced signal or filtered signal or original signal) which is higher than the threshold value in magnitude. After that, other waves are determined such as 'Q' & 'S' or 'Q' & 'R'.

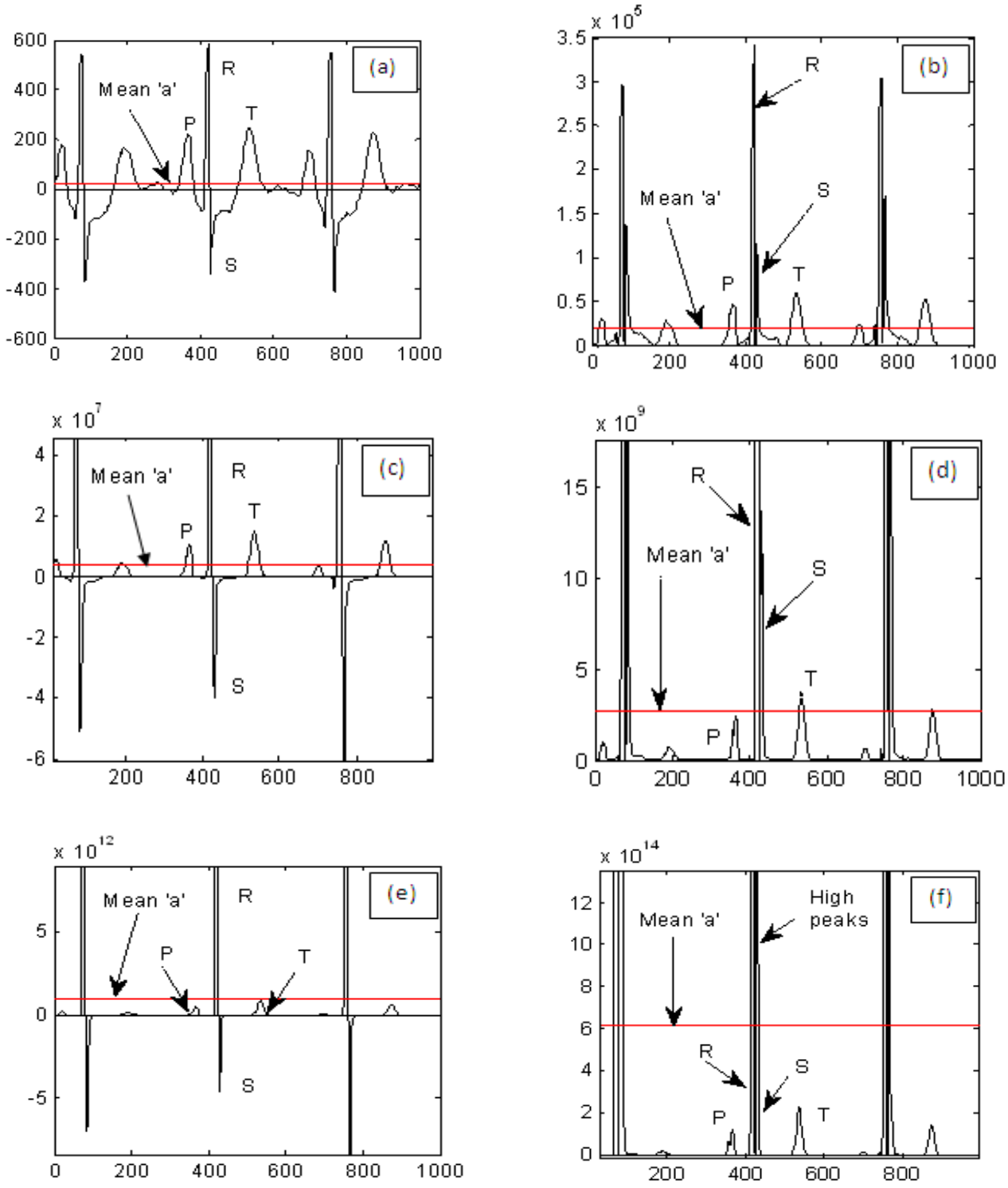

Fig. 4.1 Mean value position variation with higher power: (a) Original data. (b) Second power. (c) Third power. (d) Fourth power. (e) Fifth power. (f) Sixth power

4.3.2 QRS Detection in Single Lead System

A schematic block diagram of the proposed method for the single lead QRS detecting system is as shown in Fig. 4.2 and detailed steps with, results are described in the next section.

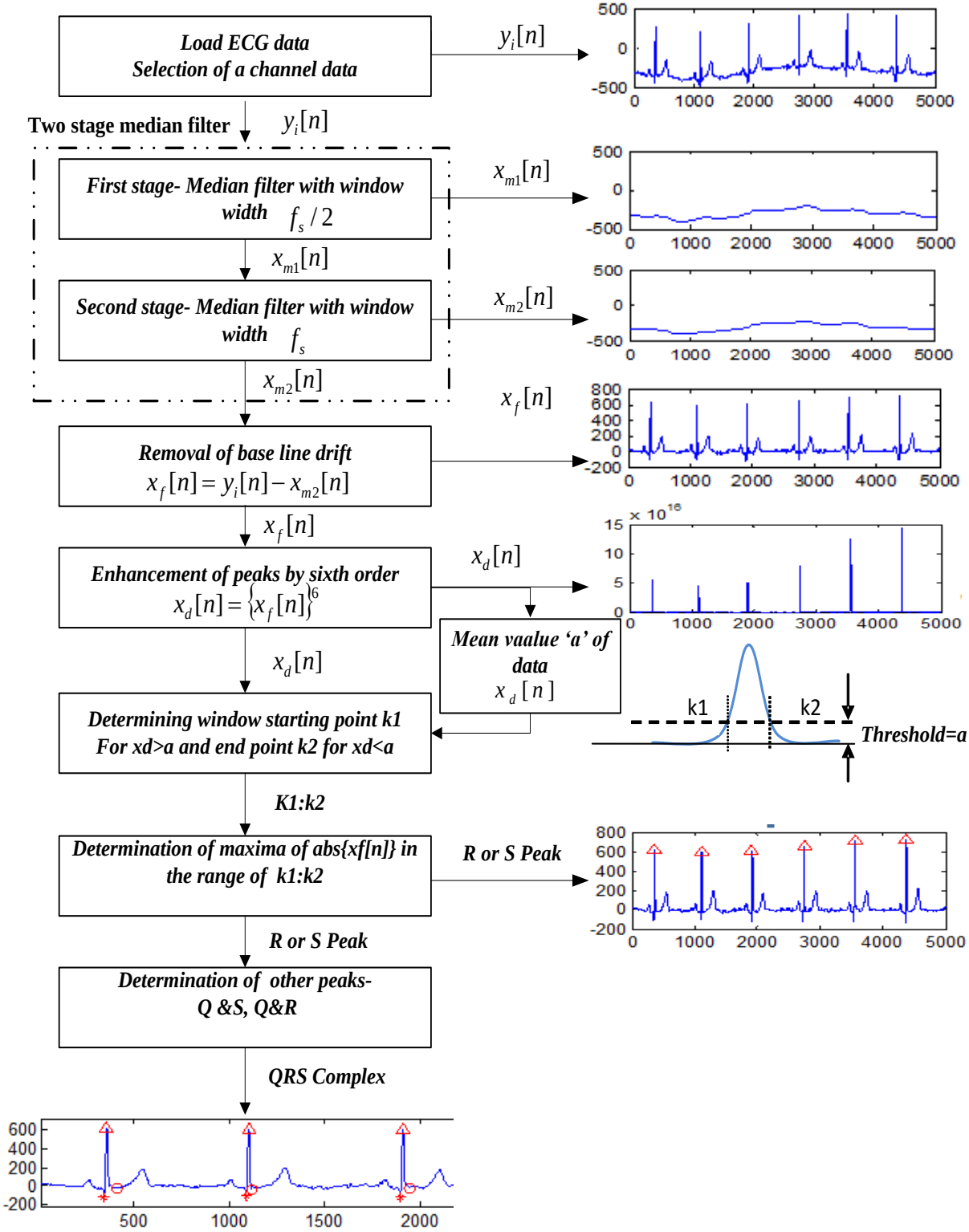

Fig. 4.2 Schematic diagram of QRS detection method in single lead

4.3.2.1 Steps for QRS detection in single lead system

1. Load ECG data (single or multi channel) having sampled frequency f_s, given by

$$\begin{bmatrix} y_1[n] \\ - \\ y_i[n] \\ - \\ y_p[n] \end{bmatrix} = \begin{bmatrix} x_{11}[n] & x_{12}[n] & x_{1m}[n] \\ - & - & - \\ x_{i1} & x_{i2} & x_{im} \\ - & - & - \\ x_{p1}[n] & x_{p2}[n] & x_{pm}[n] \end{bmatrix} \tag{4.1}$$

where $y_1[n]$, . , $y_p[n]$ represent channel data for '*p*' number of channels and $x_{11}[n]$, .., $x_{1m}[n]$ represent data values of respective channel.

2. The filtered output of data step by step shown in Fig. 4.3. Select any one channel of ECG data say, having total samples N, as shown in Fig. 4.3 (a) for N=5000.
3. Removing baseline drift, apply two stage median filter

(A) First stage median filter: using window width $f_{s/2}$.

(a) Input data $y_i[n]$ having total samples 'N' and sampling frequency f_s.

(b) In this stage, the median values of input data $y_i[n]$ are to be determined and stored in an array $x_{m1}[n]$ from 1 to $f_s/4$ points, using a variable window size of $f_s/4$ to $f_s/2$.

(c) In next stage, median values of input data $y_i[n]$ are to be determined and stored in an array $x_{m1}[n]$ from $f_s/4+1$ to $N-f_s/4$ points, using a moving window size $f_s/2$.

(d) In last stage, median values of input data $y_i[n]$ are to be determined and stored in an array $x_{m1}[n]$ from $N-f_s/4+1$ to N points, using a variable window size of $f_s/2$ to $f_s/4$. Fig. 4.3 (b) shows the plot of median values $x_{m1}[n]$.

(B) Second stage median filter: using window width f_s

(a) Take first stage data $x_{m1}[n]$ having total samples 'N'.

(b) In this stage, the median values of data $x_{m1}[n]$ are to be determined and stored in an array $x_{m2}[n]$ from 1 to $f_s/2$ points, using a variable window size of $f_s/2$ to f_s.

(c) Onthe next stage, the median values of data $x_{m1}[n]$ are to be determined and stored in an array $x_{m2}[n]$ from $f_s/2+1$ to $N-f_s/2$ points, using a moving window size f_s.

(d) In the last stage, the median values of input data $x_{m1}[n]$ are to be determined and stored an array $x_{m2}[n]$ from $N - f_s/2+1$ to N points, using a variable window size of f_s to $f_s/2$. Fig. 4.3 (c) shows the plot of median values $x_{m2}[n]$.

(e) To remove baseline drift from the signal $x_f[n]$, subtract second stage median filter output $x_{m2}[n]$ from input data $y_i[n]$, as shown in Fig. 4.3 (d).

$$x_f[n] = y_i[n] - x_{m2}[n] \tag{4.2}$$

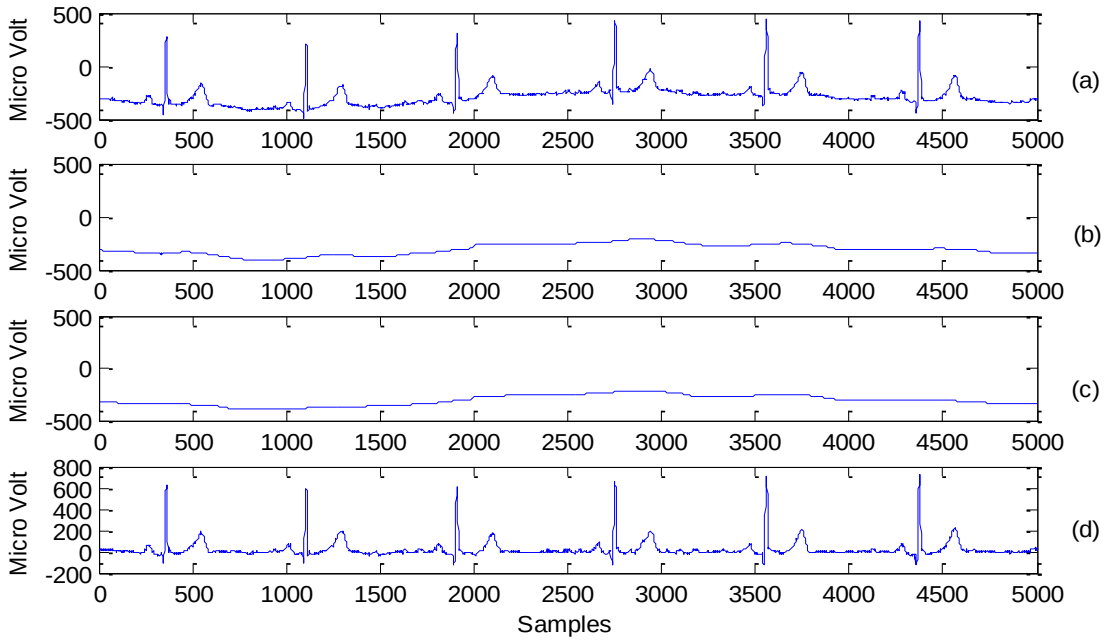

Fig. 4.3 Outputs of median filter: (a) Original signal (MO1_015, Lead I) $y_i[n]$, (b) First stage median filter output $x_{m1}[n]$, (c) Second stage median filter output $x_{m2}[n]$ and, (d) Baseline wander signal $x_f[n]$

4. An enhancement of various peaks such as P, QRS, T waves is done by using the sixth power of filtered data $x_f[n]$ and is shown in Fig. 4.4. Data $x_d[n]$ with enhanced peaks are

$$x_d[n] = \{x_f[n]\}^6 \tag{4.3}$$

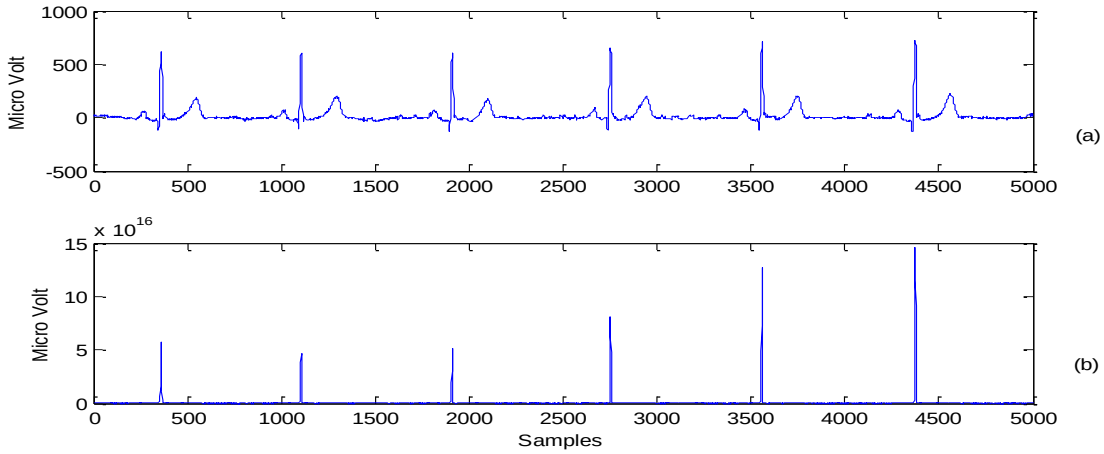

Fig. 4.4 Enhanced peaks in signal (MO1_015, Lead I): (a) Baseline wander free signal $x_f[n]$ and, (b) Data with enhanced peaks $x_d[n]$

5. Mean value of peaks enhanced data $x_d[n]$ of length 1 to 2*fs* is taken as threshold value **'a'** for starting peak.
6. Steps to determine the variable window width (k_2-k_1) as depicted in Fig. 4.5:

   (A) To determine starting point k_1 of first peak: Since the first peak, compare $x_d[n]$ to the threshold value **'a'**, if it is greater than the threshold value, then mark point k_1, as shown in Fig. 4.5 (a).

   (B) To determine ending point k_2 of first peak: For first peak, compare $x_d[n]$ from k_1 onwards to the threshold value **'a'**, if this value is less, and then mark point k_2, as shown in Fig. 4.5 (a)
7. Determine end point 'K' of current ECG cycle: Select window (k_2:(k_2+*fs*/2)) in enhanced data, determine the standard deviation of enhanced data as follows:
   (a) First 8 samples of standard deviation of input data are determined using a variable window of size 8 to 16. Similarly the last 8 samples are determined using a window size of 16 to 8.
   (b) The remaining samples in between are obtained by the standard deviation of input data with fixed size of 16. All standard deviation samples are stored in an array, and then the minima of this standard deviation is found, which is the end point k of current cycle or starting point of the next cycle of ECG wave as shown in Fig. 4.5 (b).

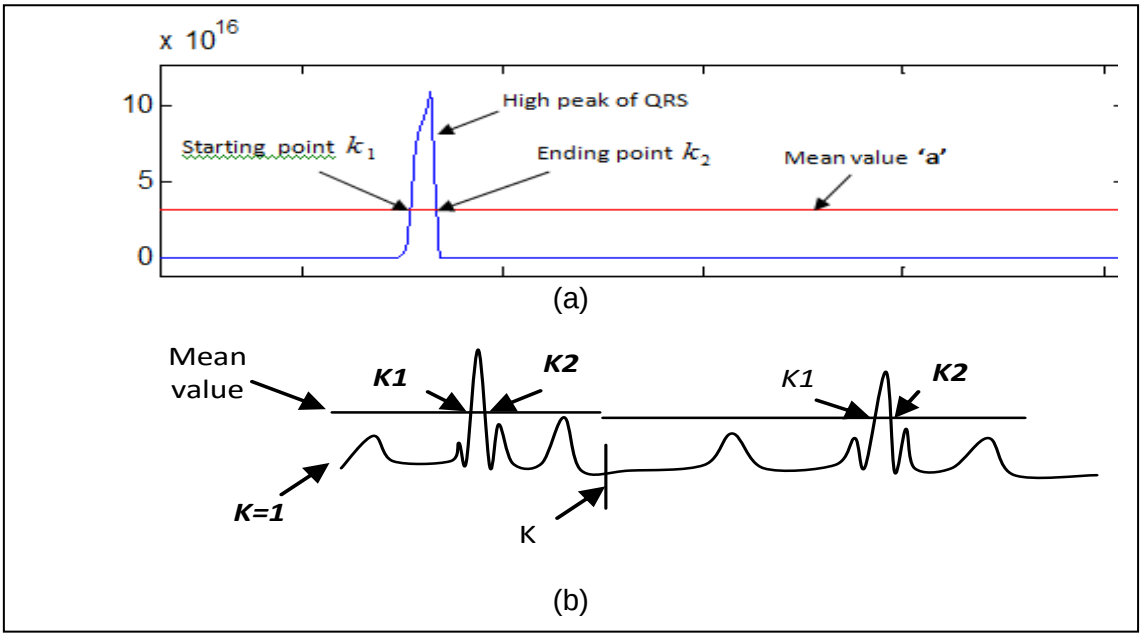

Fig. 4.5 (a) Detection of variable window point k_1 & k_2 and (b) detection of end point 'k' or starting point 'k' of the next cycle in the enhanced signal $x_d[n]$

8. Detection of QRS

(A) Detection of QRS high peak:

The window (k_1:k_2) when mapped in original or filtered data has absolute maxima or high peaks marked by the symbol (^) as shown in Fig. 4.6. If detected peak is positive, then it is 'R' otherwise 'S' wave.

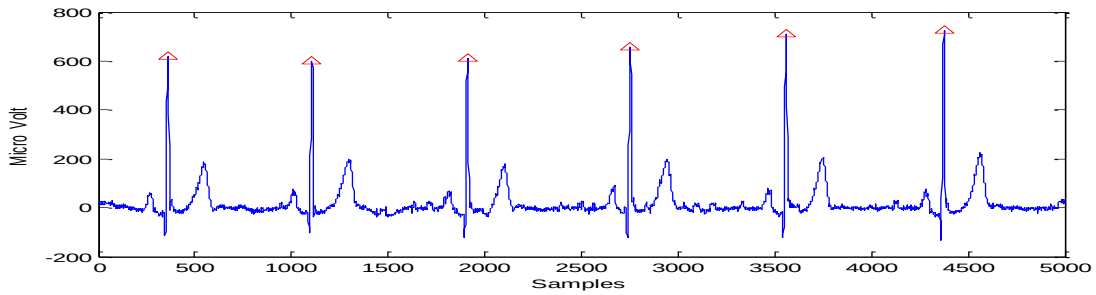

Fig. 4.6 Detection of peak in the filtered signal (MO1_015, Lead I), here R-wave peak is marked as (^)

(B) If 'R' wave peak is detected, then find other waves such as 'Q' and 'S':

(a)To determine 'Q' wave – search left side from 'R' wave up to 60 ms to find first minima.

(b) To determine 'S' wave – search right side from 'R' wave up to 60 ms to find first minima.

(C) If detected peak is 'S' wave, then find other waves such as ‘R’ and ‘Q’:

(a)To determine ‘R’ wave – search left side of 'S' wave up to 80 ms to find first maxima.

(b) To determine ‘Q’ wave – search left side of 'S' wave up to 80 ms to find first minima. The marking of ‘Q’, ‘R’, and ‘S’ waves are by the symbol ‘*’, ‘^’ and ‘o’ as shown in Fig. 4.7.

9. Adaptive threshold: After first peak detection using threshold **‘a’** (**a**=mean (1:2 times *fs*)), determine adaptive threshold **‘a’** (a=mean (enhanced data (end point of current cycle: end point of current cycle + 1.5 times *fs*))).
10. From next peak to last peak find starting point k_1 using adaptive threshold **‘a’**, starting from endpoint of previous cycles and following step 6 (A) and for ending point k_2, follow step 6 (B). Skipped period (automatically determined) is used to eliminate false peak detection due to abnormal ‘T’ wave.

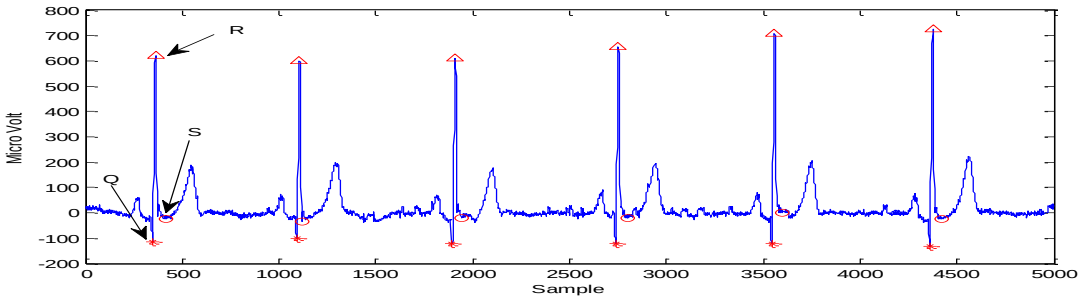

Fig. 4.7 Detection of QRS peaks in the filtered signal (MO1_015, Lead I), here Q, R, S peakis marked as ‘*’, '^’ and ‘**o**’ respectively

4.3.2.2 Experimental results and discussion

The evaluation of this proposed new method was done with various standard ECG databases, such as CSE data set-3 (MO1_001 to MO1_125), MIT/BIH Arrhythmia Database, ESC ST-T Database and QT Database. The performance of the proposed method is evaluated in terms of Sensitivity (Se) and Positive predictivity (+P) [42] given in equations (4.4) and (4.5).

$$Sensitivty\ (Se\%) = TP/(TP + FN) \tag{4.4}$$

$$Positive\ Predictivity\ (+P\%) = TP/(TP + FP) \tag{4.5}$$

where *TP*-True Positive, is being identified as correctly detected QRS, FN-False Negative being identified when the QRS is present and detector does not detect it, FP-False Positive, means QRS is not present, but detector detects QRS location. In this section, five experiments are described performing our algorithm with different types of standard databases. Kohler et al [42]. Suggested computational load as low, medium and high

according to the generation of the feature signals and complexity of techniques used, so the computational load is also considered here and performance of other detectors is then compared with the proposed method.

Experiment 1: In this experiment, CSE data set-3 original 125 cases (MO1_001 – MO1_125) only considered, and perform 12 standard lead ECG QRS detection. This database contains normal, abnormal and many heart diseases. Fig. 4.8 shows QRS detection in CSE data base record MO1_016 (Lead I). In this record variation in baseline drift is large and the proposed method is able to correctly detect all QRS locations. A summary of all 125 original cases is presented in Table 4.1. In this Table, for all 12 lead ECG used to evaluate QRS detection, and it is observed that the proposed new method detected total 55 false positives and 88 false negatives resulting in overall QRS detection sensitivity (*Se*) and positive predictivity (+*P*) of MO1 series as 99.51% and 99.69%, respectively. The false positive detection was found mainly in the ECG signals where 'P' and 'T' waves were peakier than QRS complexes. In this case, Lead I and II show more false positive and false negative than other leads due to more peaky 'P' waves and heavy noisy signals. In literature for QRS detection, Saxena et al [21] and Vijiaya et al [55] used CSE database data set-3 using artificial data, which is a single good beat of original signal repeated for ten seconds. Researcher Mehta et al [56-58] have also performed QRS detection of original CSE database data set-3. In the algorithm comparison shown in Table 4.2 with the original data set-3, performance of the proposed method is comparable and higher.

Table 4.1 Results of the QRS detection Algorithm for the CSE database data set-3 (125 original cases full length)

Lead Name	Total QRS	TP	FP	FN	Se %	+P %	Lead Name	Total QRS	TP	FP	FN	Se %	+P %
I	1497	1478	13	19	98.73	99.13	V1	1497	1494	3	3	99.80	99.80
II	1497	1476	22	21	98.60	98.53	V2	1497	1489	0	8	99.47	100.00
III	1497	1493	0	4	99.73	100.00	V3	1497	1492	0	5	99.67	100.00
aVR	1497	1493	2	4	99.73	99.87	V4	1497	1495	0	2	99.87	100.00
aVL	1497	1489	15	8	99.47	99.00	V5	1497	1492	0	5	99.67	100.00
aVF	1497	1491	0	6	99.60	100.00	V6	1497	1494	0	3	99.80	100.00
							Total	**17964**	**17876**	**55**	**88**	**99.51**	**99.69**

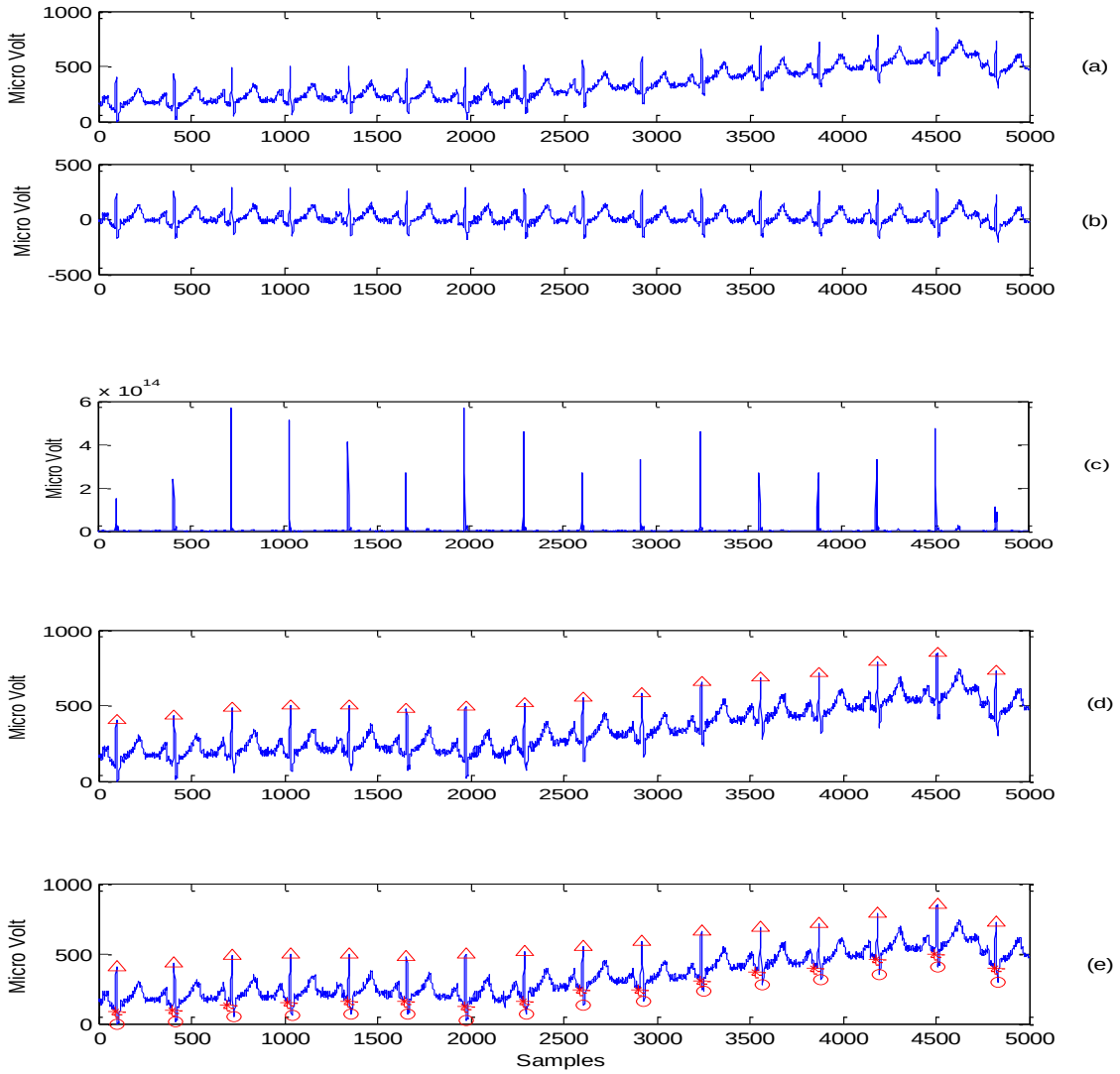

Fig. 4.8 QRS detection in MO1_016 Lead-I (a) Original data, (b) Baseline drift free signal (c) Enhanced peaks (d) Detection of maxima value of R wave (e) Marking of QRS waves as ('*','^'and '**o**')

Table 4.2 Comparison of QRS detection with another algorithm using a CSE database data set-3 (MO1_001-MO1_125)

Sl. No.	QRS Detector	Data	Cases	Using beats	TP	FP	FN	Se %	+P %	Computational Load [42]
1.	S.S. Mehta et.al [56]	DS3	125 (12_lead)	17856	17616	204	240	98.66	98.86	High
2.	Proposed Algorithm	DS3	125 (12_lead)	17964	17876	55	88	99.51	99.69	Low

Experiment 2: In this experiment, MIT/ BIH arrhythmia data were considered, which mostly contains normal, RBBB, LBBB, APC, PVC with baseline wander and artifacts. In this study, our algorithm performs QRS detection with 48 records in full length, without power noise and artifacts removing, only baseline wander removed. Some records having different diseases shown in figures from Fig. 4.9 to Fig. 4.13. MIT/BIH arrhythmia data record 103 highly baseline drifts, with noises, which is clearly detected as shown in Fig. 4.9. Fig. 4.10 depicts QRS detection performance for record 106 MIT/BIH arrhythmia data. In this data, variation of morphological, high PVC, change in amplitude and sudden change in RR interval are correctly detected. Fig. 4.11 shows record 109 where LBBB beats are clearly detected. Fig. 4.12 describes the QRS detection in record 119 MIT/BIH arrhythmia data, which has wide PVCs and variation in RR interval. Fig. 4.13 represents the QRS detection in record 212 MIT/BIH arrhythmia data, which has RBBB beats clearly detected.

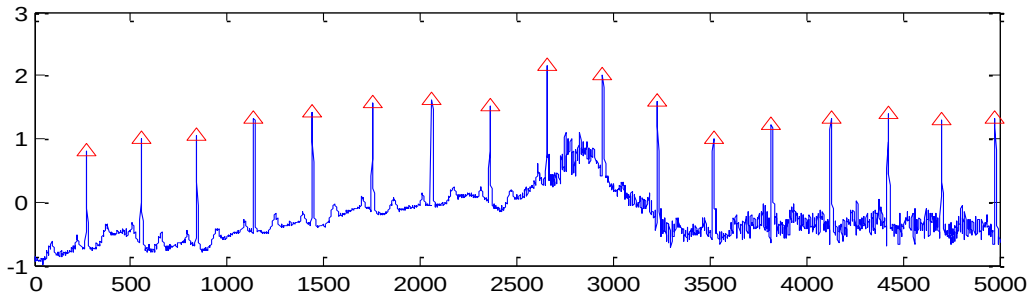

Fig. 4.9 QRS detection in MIT/BIH 103 first lead (ML-II)

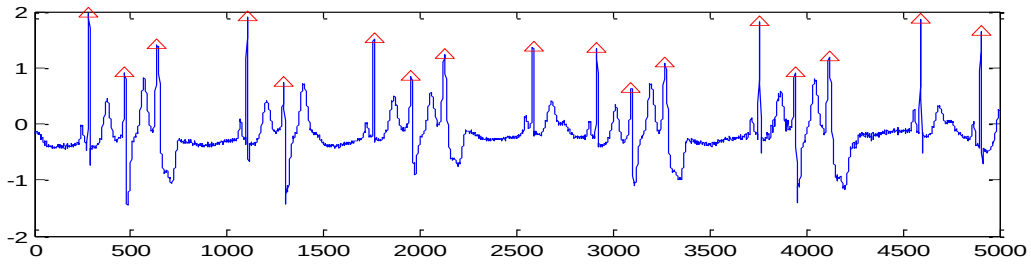

Fig. 4.10 QRS detection in MIT/BIH 106 first lead (ML-II)

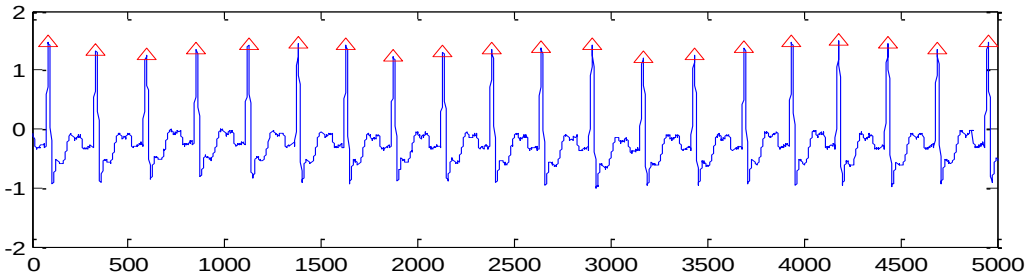

Fig. 4.11 QRS detection in MIT/BIH 109 LBBB first lead (ML-II)

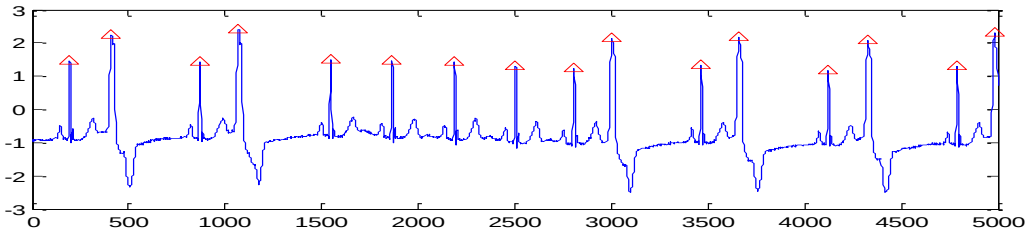

Fig. 4.12 QRS detection in MIT/BIH 119 first lead (ML-II)

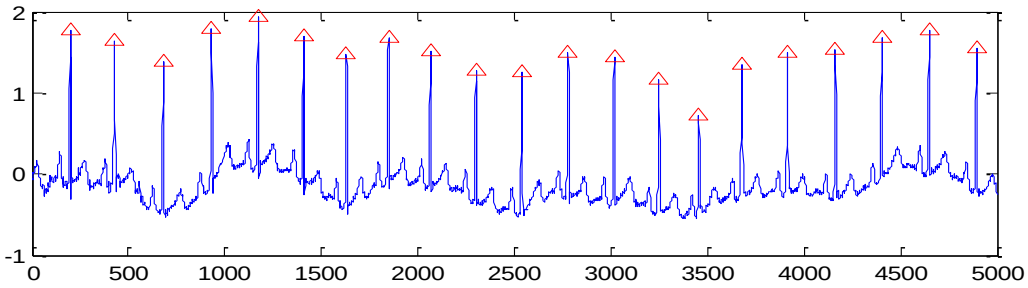

Fig. 4.13 QRS detection in MIT/BIH 212 RBBB first lead (ML-II)

In the given literature many researchers developed QRS detector where they mostly evaluated the performance of method by using MIT/BIH arrhythmia database. In literature almost all researchers used single first annotated lead data for QRS detection. In Table 4.3 we observe that performance of all 48 records of first lead is good and within the limit of required QRS detection. The proposed new method detected total 728 false positives and 870 false negatives resulting in overall QRS detection sensitivity (Se%) and positive predictivity (+P%) of MIT/BIH A D as 99.21% and 99.34%, respectively, which is higher and comparable to other methods.

Table 4.3 Comparison of QRS detection with other algorithms using MIT/BIH AD database

S. No.	QRS Detector	Cases	Using beats	TP	FP	FN	Se %	+P %	Computational Load [42]
1	Yeh et al [43]	48	109809*	109643	58	166	99.85	99.95	Low
2	Pan and Tompkins [45]	48	109809*	109208	507	277	99.75	99.54	High
3	Hamilton & Tompkins [46]	48	109267	108927	248	340	99.69	99.77	Medium
4	Adnane et al [47]	48	109494	109241	393	253	99.77	99.64	Low
5	Saxena et al [21]	48	103763	103664	102	99	99.90	99.90	Medium
7	Ghaffari et al [51]	48	110159	109837	322	120	99.89	99.71	High
8	Ghaffari et al [52]	48	109428	109327	129	101	99.91	99.88	High
9	Chouakri et al[54]	48	109488	108043	3068	1446	98.68	97.24	High
10	Zhang et al [58]	48	109510	109297	204	213	99.81	99.81	Medium
11	Christov [60] Alg-I	48	110050	109548	215	294	99.69	99.69	Medium
12	Christov [60] Alg-II	48	110050	109615	239	240	99.74	99.65	Medium
13	Chen et al [61]	48	110050	109615	239	24	99.78	99.78	Medium
14	**Proposed method**	**48**	**109966**	**109096**	**728**	**870**	**99.21**	**99.34**	**Low**

* Values computed according to the record-record tables in the referred works since there is a discrepancy between total values and the sum of the individual ones.

Experiment 3: In this experiment, ESC ST-T database was used and QRS detection was performed on 90 ECG records. This database contains normal, abnormal and variation in ST-T interval and T wave morphology. Fig. 4.14 shows QRS detection in record e0105 (MLIII), in which variation in T wave is larger than R peak. In this experiment proposed method is able to correctly detect QRS locations. Summary of all 90 cases is represented in Table 4.4. In this Table, all cases used first lead to evaluate QRS detection and we observe that the proposed new method detected total 2,190 false positives and 3,679 false negatives resulting in overall QRS detection sensitivity (Se) and positive predictivity (+P) of ESC ST-T as 99.53% and 99.72% respectively, which is comparable and higher than other methods.

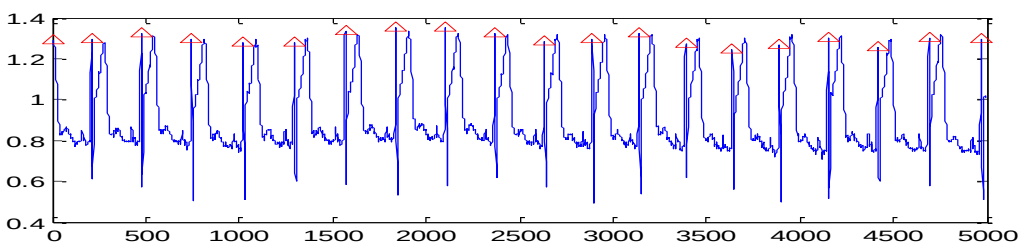

Fig. 4.14 QRS detection in data e0105 (MLIII)

Table 4.4 Comparison of QRS detection with another algorithm using ESC-ST-T database

S. No.	QRS Detector	Data	Cases	Using beats	TP	FP	FN	Se %	+P %	Computational Load [42]
1	Martinez et al [50]	ESC ST-T	90	787103	784059	4077	3044	99.61	99.48	High
2	Ghaffari et al [52]	ESC ST-T	90	787103	784210	3554	2893	99.63	99.55	High
3	**Proposed method**	**ESCST-T**	**90**	**790559**	**774180**	**2190**	**3679**	**99.53**	**99.72**	**Low**

Experiment 4: In this experiment, QT database was used and QRS detection was performed on 105 ECG records. This database contains normal, abnormal and variation in the QRS, ST-T interval and T wave morphology. Table 4.5 depicts the overall performance of the proposed method which detected total 41 false positives and 107 false negatives resulting in overall QRS detection sensitivity (Se) and positive predictivity (+P) of QT database as 99.87% and 99.95%, respectively, which is higher and comparable to other methods.

Table 4.5 Comparison of QRS detection with another algorithm using the QT database

S. No.	QRS Detector	Data	Cases	Using beats	TP	FP	FN	Se %	+P %	Computational Load [42]
1	Martinez et al [50]	**QT**	105	86892	86824	107	68	99.92	99.88	High
2	Ghaffari et al [52]	**QT**	105	86892	86845	79	47	99.94	99.91	High
3	**Proposed method**	**QT**	**105**	**87679**	**87572**	**41**	**107**	**99.87**	**99.95**	**Low**

The comparison of QRS detection performance of the proposed method with other methods using standard database of CSE, MIT/BIH and CSE_ST-T database is shown in Table 4.2, Table 4.3, Table 4.4 and Table 4.5 respectively. Table 4.6 represents the overall performance of the proposed method, using four different standard databases, with 368 cases and total 10,06,168 beats analysis. The overall average sensitivity of 99.52% and positive predictivity of 99.69% was achieved considering all four standard databases.

The new method was implemented by using MATLAB 7.8.0 (2009a) Software on a PC with Intel Core 2 Duo 2.67 GHz processor. The average computational times for CSE, MIT/BIH AD and ESC ST-T full length data are 0.5-0.8s, 80-85s and 230-250s respectively.

Table 4.6 Results summary of the QRS detection for the CSE, MIT/BIH AD, ESC-ST-T and QT database

S. No.	Data	Cases	Using beats	TP	FP	FN	Se %	+P %
1	CSE DS-3	125	17964	17876	55	88	99.51	99.69
2	MIT/BIH	48	109966	109096	728	870	99.21	99.34
3	ESC ST-T	90	790559	774180	2190	3679	99.53	99.72
4	QT	105	87679	87572	41	107	99.87	99.95
Total		**368**	**1006168**	**988724**	**3935**	**4892**	**99.52**	**99.69**

Experiment 5: In this section two example performances related to noise handling problems are presented, in order to understand how the SNR affects the performance of the QRS detector. One example was performed using zero mean, white Gaussian noise with variance, to find QRS detection rate [61] by selecting the varying SNR values from 0 – 15dB. Table 4.7 depicts the experimental performance of the proposed algorithm with varying SNR of record 119 of MIT/BIH arrhythmia database. Comparison of QRS detection rate performance with another algorithm is represented in Table 4.8. Observing the results in Table 4.7 & Table 4.8, we find that a QRS detection rate of 100% could be achieved at SNR 11dB by proposing algorithm which is comparable to other algorithms [61]. Fig. 4.15 shows the QRS detection algorithm for a data record 119 at different level of SNR.

Table 4.7 SNR versus QRS detection rate Algorithm for the record 119 MIT/BIH AD

SNR(dB)	Total QRS	TP	FP	FN	Se (%)	+P (%)	Min (Se+P) [61]
0	22	3	41	19	13.64	6.82	6.82
1	22	5	38	17	22.73	11.63	11.63
2	22	5	37	17	22.73	11.90	11.90
3	22	6	32	16	27.27	15.79	15.79
4	22	9	28	13	40.91	24.32	24.32
5	22	10	22	12	45.45	31.25	31.25
6	22	13	20	9	59.09	39.39	39.39
7	22	13	19	9	59.09	40.63	40.63
8	22	15	13	7	68.18	53.57	53.57
9	22	19	5	3	86.36	79.17	79.17
10	22	19	5	3	86.36	79.17	79.17
11	22	22	0	0	100.00	100.00	100.00
12	22	22	0	0	100.00	100.00	100.00
13	22	22	0	0	100.00	100.00	100.00
14	22	22	0	0	100.00	100.00	100.00
15	22	22	0	0	100.00	100.00	100.00

Table 4.8 Comparison of QRS detection rate with other algorithm using varying SNR for the record 119 MIT/BIH AD

	Proposed algorithm			Chen et al [61]		
SNR(dB)	Se (%)	+P (%)	Min (Se+P) [61]	Se (%)	**+P**(%)	Min (Se+P) [61]
0	13.64	6.82	6.82	93.85	92.82	92.82
1	22.73	11.63	11.63	97.21	95.87	95.87
2	22.73	11.90	11.90	97.77	99.15	97.77
3	27.27	15.79	15.79	99.16	99.16	99.16
4	40.91	24.32	24.32	99.72	99.17	99.17
5	45.45	31.25	31.25	100.00	98.9	98.9
6	59.09	39.39	39.39	100.00	99.44	99.44
7	59.09	40.63	40.63	100.00	99.44	99.44
8	68.18	53.57	53.57	100.00	99.72	99.72
9	86.36	79.17	79.17	100.00	99.72	99.72
10	86.36	79.17	79.17	100.00	99.72	99.72
11	100.00	100.00	100.00	100.00	99.72	99.72
12	100.00	100.00	100.00	100.00	99.72	99.72
13	100.00	100.00	100.00	100.00	99.72	99.72
14	100.00	100.00	100.00	100.00	99.72	99.72
15	100.00	100.00	100.00	100.00	100.00	100.00

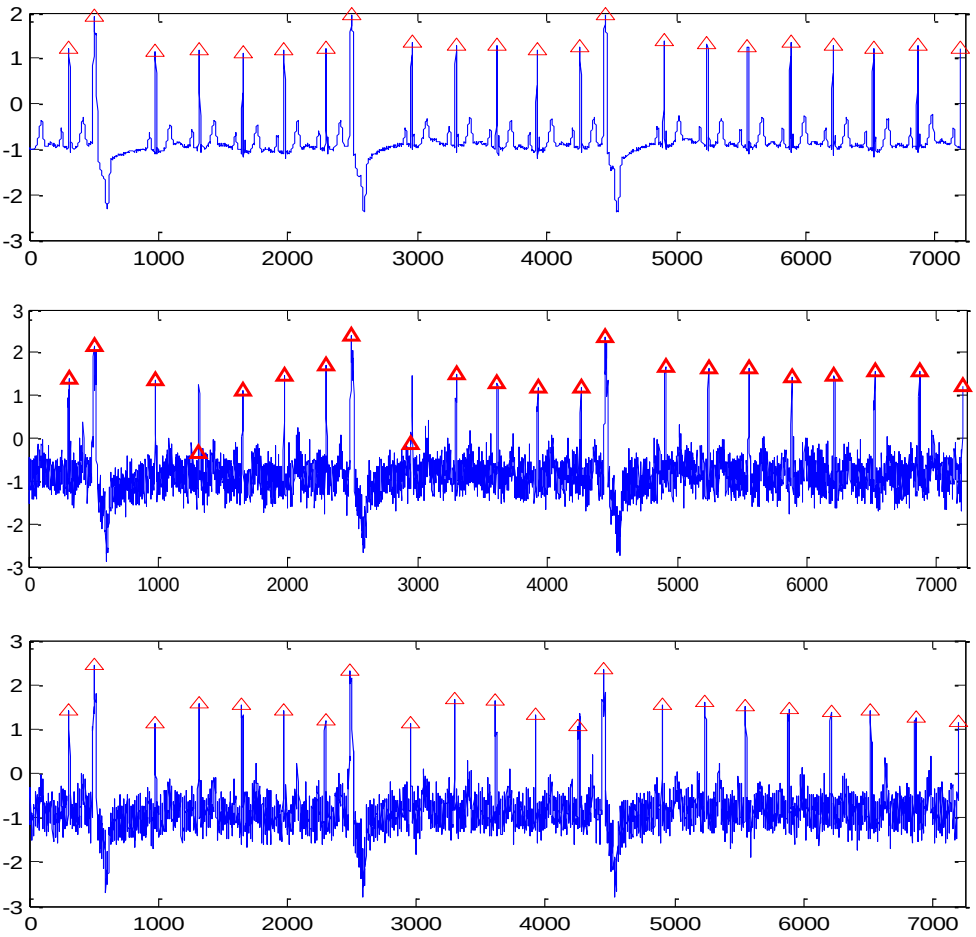

Fig. 4.15 QRS detection of record 119 (MLIII) MIT/BIH arrhythmia database at different level of SNR: (Top) QRS detection of the original data without adding noise, (Middle) QRS detection at SNR 11dB, and (Bottom) QRS detection at SNR 12dB

In this section another example of QRS detection was performed on 12 datasetsnoisy, full lengths (118e24 to 118e_06 and 119e24 to 119_06) from MIT-BIH Noise Stress Test Database. Experimental results of QRS detection performance of the proposed algorithm are depicted in Table 4.9, in which sensitivity of data record 118 varies from 99.69% to 72.43% for SNR 24 dB to -6 dB. Similarly, sensitivity of data record 119 varies from 100.00% to 72.62% for SNR 24 dB to -6 dB. This performance is higher [62] and comparable [63,65] to other algorithms shown in Table 4.10.

Table 4.9 Algorithm performance for the record MIT/BIH Noise stress database 118 and 119

Data Name	Total QRS	TP	FP	FN	Se %	+P %	Data Name	Total QRS	TP	FP	FN	Se %	+P %
118e24	2278	2271	7	7	99.69	99.69	119e24	1987	1987	1	0	100.00	99.95
118e18	2278	2216	66	62	97.28	97.11	119e18	1987	1980	7	7	99.65	99.65
118e12	2278	2149	138	129	94.33	93.96	119e12	1987	1907	95	80	95.97	99.25
118e06	2278	1941	278	337	85.21	87.47	119e06	1987	1952	268	253	88.17	86.73
118e00	2278	1732	440	546	76.03	79.74	119e00	1987	1531	453	456	77.05	77.73
118e_6	2278	1650	508	628	72.43	76.45	119e_6	1987	1443	545	544	72.62	72.56

Table 4.10 Comparison of QRS detection performance with other algorithms using MIT/BIH Noise stress Database

Data Name	Total QRS	Proposed method		Plesnik et al [62]		Benitez et al. [63]		H. Li and J. Tan [65]			
								Algorithm-I		Algorithm-II	
		Se %	+P %	Se %	+P %	Se %	+P %	Se %	+P %	Se %	+P %
118e24	2278	99.69	99.69	98.46	100.00	100.00	100.00	99.32	99.79	100.00	99.64
118e18	2278	97.28	97.11	97.76	99.96	99.96	99.82	98.49	99.00	100.00	99.46
118e12	2278	94.33	93.96	88.98	96.99	98.81	97.28	96.66	97.78	99.90	89.32
118e06	2278	85.21	87.47	68.70	84.96	94.69	91.13	91.23	81.11	99.63	73.34
118e00	2278	76.03	79.74	43.59	61.56	84.15	82.66	77.30	71.34	99.53	57.68
118e_6	2278	72.43	76.45	25.37	54.37	78.45	77.16	63.47	72.04	89.93	52.01
119e24	1987	100.00	99.95	99.85	99.95	100.00	99.95	100.00	98.17	100.00	99.58
119e18	1987	99.65	99.65	99.80	99.95	99.95	99.80	99.28	98.04	99.88	98.99
119e12	1987	95.97	99.25	96.28	99.07	99.14	95.12	98.25	97.37	99.28	88.52
119e06	1987	88.17	86.73	81.03	89.54	95.87	88.85	96.33	89.99	99.63	70.24
119e00	1987	77.05	77.73	41.92	58.74	89.73	81.34	89.58	75.38	99.28	53.38
119e_6	1987	72.62	72.56	23.65	44.76	81.08	74.17	78.09	66.27	98.01	49.14

4.3.2.3 Conclusion of single lead QRS detection

An effective and reliable QRS detection method based on peak enhancements by the sixth powerof the signal and variable window width has been presented here. This proposed new method was tested on various standard databases such as CSE, MIT/BIH, ESC ST-T and QT database and obtained good results & statistical indices are higher or comparable to

those cited in the literature. The proposed method is very simple, fast and reliable to determine QRS at different sampling frequency rates without using any denoising software. In this study, we used only baseline wander by using two stage median filters, and signal enhanced by the sixth power of a signal. In case of even noisy signal, QRS detection was achieved, which was verified at various SNR values. The algorithm was tested on different SNR values with 12 data of the MIT-BIH Noise Stress Test Database. The QRS detection performance achieved was higher and comparable to other algorithms. In this method I observed that QRS detector works accurately even at different sampling frequencies. This method is applicable for designing composite heart disease analyzer, such as ST segment and arrhythmia monitoring.

4.3.3 QRS detection in Multilead (12-Lead ECG)

In the past few decades, increasing application has been forced on the use of multilead monitoring for telemetry and ambulatory electrocardiography. There are reliable advantages of multilead monitoring for the detection and positioning of acute ischemia in patients with coronary artery disease. These techniques are also important for the detection and accurate diagnosis of arrhythmias, because multilead ECG recordings provide important information of P wave and QRS complex morphology that cannot be determined from two or three lead recordings. This results in a measurable change in potential difference on the body surface of the subject. Multilead (12-lead) ECG recording represents a powerful signal acquisition method that can be used for patient monitoring, ambulatory recording or telemetry, for exercise testing electrocardiography. In ischemia, 12-lead ECG monitoring provides increased sensitivity for the ST segment elevation pattern that occur with acute coronary syndromes such as myocardial infarctions. Multilead also can enhance the sensitivity of ECG for the ST segment pattern of subendocardial ischemia found during ambulatory recording and during exercise testing. Similarly with respect arrhythmias, 12-lead ECG recordings can recognize "typical" from "atypical" atrial flutter. These multilead ECG recording improve the morphological characterization of ventricular tachycardia. Multilead ECGs a are necessary for quantification of the temporal variability of QT dispersion, and redundant information can often clarity artifacts that appear in individual leads. Fig. 4.16 depict 12-lead ECG data, in this recording each lead represents cardiac function in different angles.

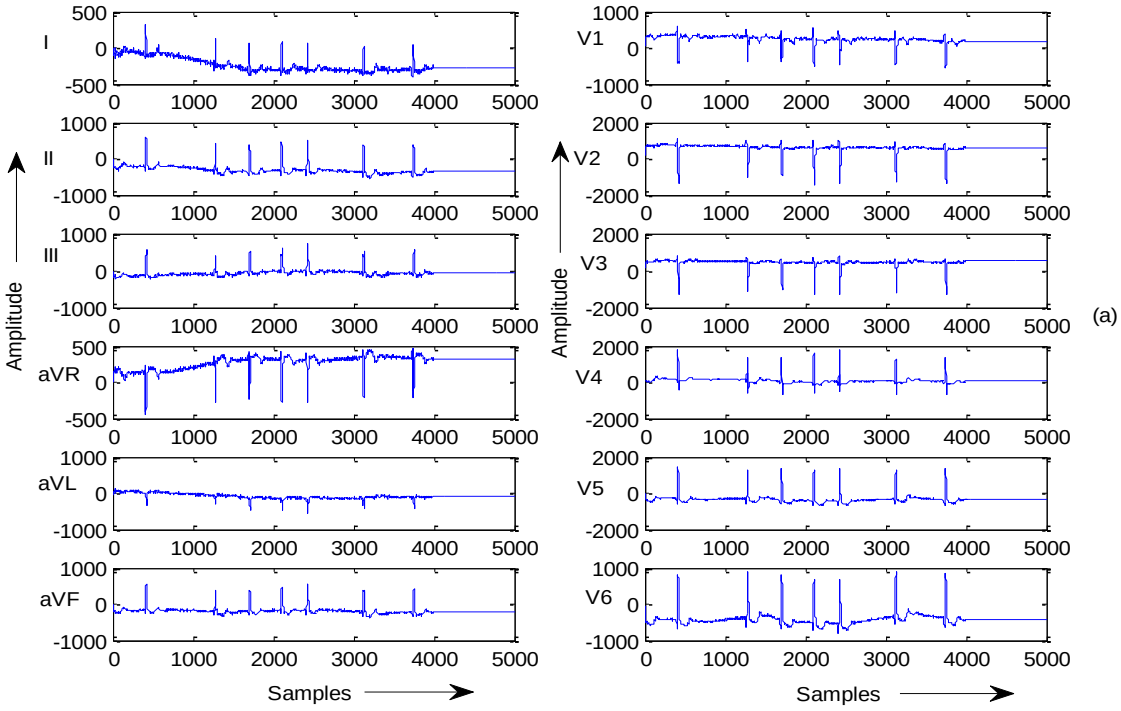

Fig. 4.16 12 Lead ECG data presentation

In the multilead ECG analysis, the simultaneous leads are transformed into a detection function. The transformation of ECG signal brings out only QRS complexes amongst the other signal, and increase QRS detection rate. Generally, transformation is used in spatial velocity functions for VCG or 12-lead ECG. Mostly, the spatial velocity function has been computed by combining the derivatives of all VCG or ECG leads. In the CSE pilot study different methods are used by researchers for various VCG and ECG programs. Once a spatial velocity function of the QRS complex is detected, after that, most algorithms apply further rules for QRS complex detection.

The multilead QRS detection is mostly divided in two parts: preprocessing stage and decision rules stages. The pre-processing stage using linear, nonlinear filters and some denoising techniques [24, 27, 29, 31] for removing noise and artifacts from the ECG signal, for enhancement of QRS region. After that decision rules identifies QRS and non QRS regions, and then locates the position of QRS.

Only a few researchers of these ECG computer programs have published detailed evaluation results of their detection methods. Bemmel et al [4, 23] published detailed evaluation results of their detection methods for multilead QRS detection. The author presents simultaneous ECG lead, VCG lead and simultaneous multilead ECG to find R peak using CSE database. In summary detection of R peaks results are (i) 11369 beat CSE 3 simultaneous ECG lead used and find R 99.6%. (ii) 2847 beats CSE 3 simultaneous VCG lead used and find R 99.9%. (III) 2889 beats CSE 3 simultaneous multi-lead lead used and

find R 100%. Kohler, et al [42] presents study of different methods of QRS detection. In this study mostly single lead QRS detector based on high-pass filters, band pass filters, and wavelet transforms, artificial neural networks, genetic algorithm and mathematical morphology has been used. Only length and energy transform method is used in both single and multilead QRS detection. Gritzali [83] proposed two methods for single lead and multilead QRS detection based on length transformation and energy transformation. The author reported QRS detection rate using CSE data set-1 for the length transformation of single and multichannel (i.e. 3-Lead) and energy transformation for multichannel are 90.66%, 99.87% and 99.13% respectively. Kyrkos *et al* [80] developed QRS detection for both three-Lead and single-Lead ECG signals using time recursive prediction techniques. Author reported QRS detection accuracy 99.00% with the CSE data set-1. Laguna *et al* [81] proposed multilead QRS detector on the basis of single-lead QRS detector [21], applying a multilead (15-lead) QRS detection rule to consider QRS in each lead whose position do not differ by more than 90 milliseconds from one lead to another and author reported wave boundaries in multilead ECG signals within range. Maheshwari *et al.* [20] reported a spatial velocity approach for detection of the QRS complexes and other component waves. Mehta and Lingayat [82] proposed the detection of QRS complexes in 12-Lead ECG using SVM and reported a QRS detection rate of 99.97% using CSE data set-3 (MO1_001 to MO1_125). These existing algorithms determine QRS complex assuming a noise free ECG signal and suppression of P & T waves by using filters based on differentiation principle. Method [56, 82] requires filtering and exhaustive training, settings, and estimation of model parameters. Most of these techniques for QRS detection are complicated as they are computationally complex and time consuming.

4.3.3.1 QRS detection method in 12-Lead ECG

Basically, QRS detection process consists of two steps: (1) filtering of signal and (2) identifying the QRS region. The Raw ECG signal has noises due to the interference of 50/60 Hz to power line and due to muscle tremor (electromyogram noise), both of which belong to high frequency noise. In addition, there are low frequency noises due to sudden patient movement or breathing and due to bad electrode, in which baseline wander frequency is lower than 1 Hz. In this study for removing baseline wander for all 12 Lead ECG, we considered two stage median filter using window widths *fs*/2 and *fs*. Median filter is a nonlinear filter which is simple to operate with high speed. The proposed QRS detection method employs a simple two stage median filter for removing baseline drift by using two window widths related to the sampling frequency of recorded all 12 Lead ECG data. In this method all 12 ECG signal added and averaged according to sample value positions, so that we can obtain composite lead signal (average signal of 12-leads). The ECG signals when contaminated by noise, have revealed better performance using coherent averaging. The

composite signal is smoothened by adding all lead at the same sample position and averaging the signal. Therefore, in this method other filter is not required to remove interference of 50/60 Hz to he power line. The obtained composite lead signal is now smoother and enhanced than other 12-leads ECG as depicted in Fig. 4.17. Detection criteria for complex localization are according to composite lead and peak amplitudes in order to avoid the false positive detection of tall P and T waves. After that, baseline drift and artifacts free smooth composite lead signal is further enhanced by point to point six times data multiplication where the sharp peaks such as Q, R, S are more enhanced than artifacts and P & T waves. Detail steps of preprocessing are explained in the next section.

Preprocessing: The recorded ECG signal contains (a) 50 or 60Hz line interference due to power line, (b) electromyogram noise due to muscle tremor which belongs to high frequency noise, (c) baseline wander due to sudden patient movement or breathing and (d) motion artifact due to the motion of the electrode, raw signals being depicted in Fig. 4.17 (a). baseline wander and motion artifact belong to low frequency in which the wander baseline drift frequency is lower than 1 Hz. In this proposed method for removing baseline wander for each ECG signal, we considered two stage median filter using window widths $f_s/2$ and f_s and filtered each ECG signal shown in Fig. 4.17 (b). Median filter is a nonlinear filter which is simple to operate with high speed [151].

Composite lead signal generation**:** In this method all filtered 12 lead ECG signals are added sample by sample and divided by 12 to generate composite lead signal. This generated new ECG signal reduces noise and is more enhanced than other 12 ECG signals and also contains all ECG wave components such as P- wave, QRS complex and T-wave in enhanced shape as shown in Fig. 4.17 (c). The morphology of composite lead signal consists of all ECG complexes such as P, QRS and T wave, similar to 12-Lead ECG system. The ECG wave complexes in composite lead signal are noise free and more enhanced in comparison to all 12 leads [152].

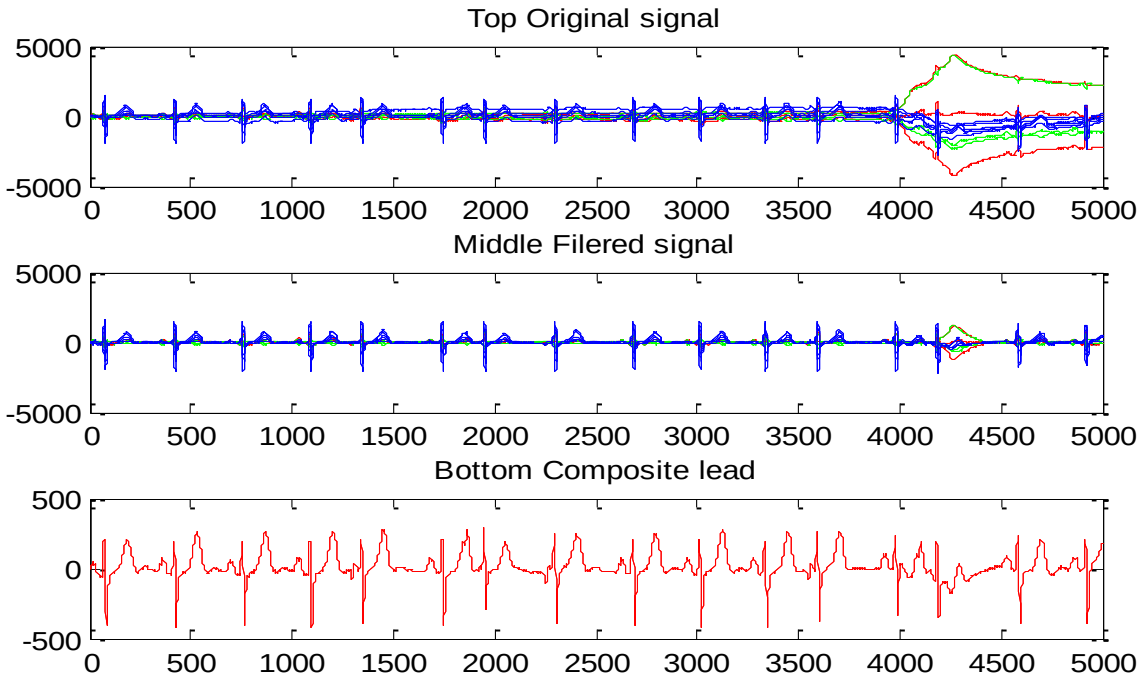

Fig. 4.17 Top to bottom (a) Raw 12 lead ECG signal, (b) baseline wander free signal (c) Composite lead signal

A schematic block diagram of the proposed method for QRS detection and boundary marking in 12-Lead ECG systems is depicted in Fig. 4.18, which consists of two stage median filters, composite lead generation, Enhancement of composite lead, determination of variable window size by using the mean of enhanced composite lead and determines the location of high peak value in the complex region.

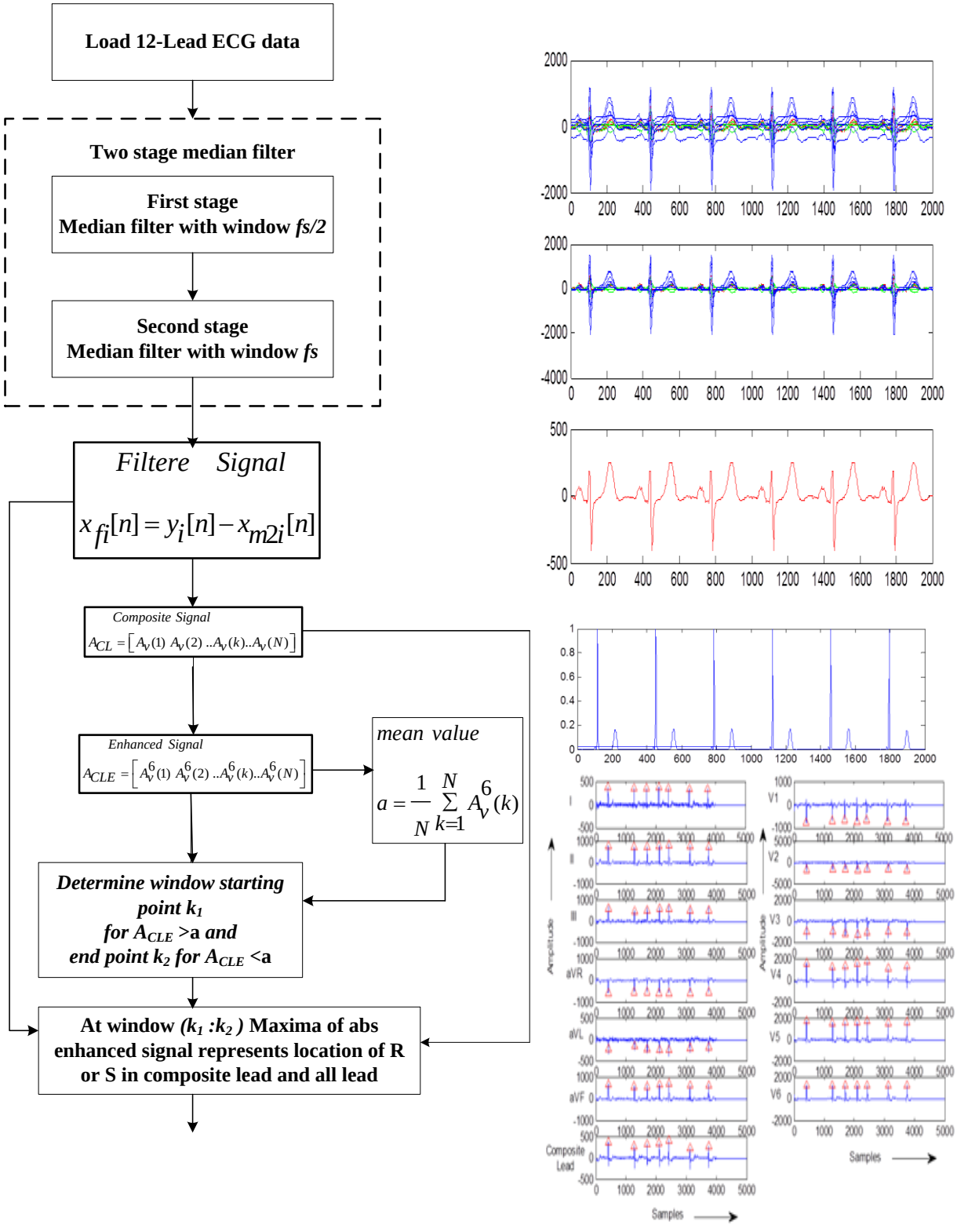

Fig. 4.18 Block diagram of multilead QRS detection method.

4.3.3.2 Steps for QRS detection in 12-Lead ECG lead system

The QRS detection, detailed steps are described as follows:

1. Load 12-Lead ECG data, as shown in Fig. 4.18 having sampled frequency f_s and number of total samples N of each data given by

$$\begin{bmatrix} y_1[n] \\ - \\ y_i[n] \\ - \\ y_{12}[n] \end{bmatrix} = \begin{bmatrix} x_{1,1}[n] & x_{1,k}[n] & x_{1,N}[n] \\ - & - & \\ x_{i,1}[n] & x_{i,k}[n] & x_{i,N}[n] \\ - & - & \\ x_{12,1}[n] & x_{12,k}[n] & x_{12,N}[n] \end{bmatrix} \quad (4.6)$$

Where $y_1[n], y_2[n]. . , y_{12}[n]$ represent 12-Lead ECG data and $x_{1,1}[n]$, .., $x_{1,N}[n]$ represent respective data values.

2. Select a channel of ECG data say $y_i[n]$.
3. Apply two stage median filter to remove baseline drift

(A) First stage median filter: using window width $f_s/2$

(a) Input data $y_i[n]$ having total samples 'N' and sampling frequency f_s

(b) In this stage median value of input data $y_i[n]$ to be determined and stored in an array $x_{m1i}[n]$ from 1 to $f_s/4$ points using a variable window size from $f_s/4$ to $f_s/2$ by increasing one by one sample.

(c) In next stage median values of input data $y_i[n]$ to be determined and stored in an array $x_{m1i}[n]$ from $f_s/4+1$ to $N-f_s/4$ points using a moving window size $f_s/2$.

(d) In last stage median values of input data $y_i[n]$ to be determined and stored in an array $x_{m1i}[n]$ from $N-f_s/4+1$ to N points, using a variable window size from $f_s/2$ to $f_s/4$.

(B) Second stage median filter: using window width f_s

(a) Take first stage data $x_{m1i}[n]$ having total samples 'N'.

(b) In this stage median value of data $x_{m1i}[n]$ to be determined and stored in an array $x_{m2i}[n]$ from 1 to $f_s/2$ points using a variable window size of $f_s/2$ to f_s.

(c) In next stage median values of data $x_{m1i}[n]$ to be determined and stored in an array $x_{m2i}[n]$ from $f_s/2+1$ to $N-f_s/2$ points using a moving window size f_s.

(d) In last stage median values of input data $x_{m1i}[n]$ to be determined and stored in an array $x_{m2i}[n]$ from $N - f_s/2+1$ to N points using a variable window size of f_s to $f_s/2$.

(e) To remove baseline drift from signal $x_{fi}[n]$ subtract second stage median filter output $x_{m2i}[n]$ from input data $y_i[n]$.

$$x_{fi}[n] = y_i[n] - x_{m2i}[n] \tag{4.7}$$

Similarly find other remaining lead data. All 12-Lead ECG filtered data are shown in Fig. 4.18.

4. Generation of composite (complex) lead data:

(a) All 12-Lead ECG filtered data are given by

$$\begin{bmatrix} x_{f1}[n] \\ . \\ x_{fi}[n] \\ . \\ x_{f12}[n] \end{bmatrix} = \begin{bmatrix} x_{f1,1}[n] & & x_{f1,k}[n] \ldots x_{f1,N}[n] \\ . & . & . \quad \ldots \\ x_{fi,1}[n] & & x_{fi,k}[n] \ldots x_{fi,N}[n] \\ . & . & . \quad \ldots \\ x_{f12,1}[n] & & x_{f12,k}[n] \ldots x_{f12,N}[n] \end{bmatrix} \tag{4.8}$$

(b) To determine the simultaneous space average $A_v(k)$ of the composite (complex) lead signal taking average of all lead data at each sample position and take the simultaneous space average value $A_v(k)$ of all lead data at k^{th} position given by

$$A_v(k) = \frac{1}{12}\left[\sum_{i=1}^{12} x_{fi,k}[n]\right] \tag{4.9}$$

Composite (complex) lead signal A_{CL} given by

$$A_{CL} = \left[A_v(1)\ A_v(2)\ ..A_v(k)..A_v(N)\right] \tag{4.10}$$

This composite lead signal is similar to other 12-Lead ECG system and consists of all complexes such as P, QRS and T waves. In this signal QRS complex region more enhanced than P and T waves in other 12-Leads ECG system. P and T wave region also smoothed. Composite Lead wave form and morphology is approximately same as other 12-Leads.

5. Again enhancement of various peaks such as P, QRS, T waves is done by taking the sixth power of composite signal A_{CL}. The enhanced composite signal signal is given by

$$A_{CLE} = \left[A_v^6(1)\ A_v^6(2)\ ..A_v^6(k)..A_v^6(N)\right] \quad (4.11)$$

6. Mean value '*a*' of enhanced composite signal A_{CLE} of length 1 to $2f_s$ is given by

$$a = \frac{1}{N}\sum_{k=1}^{N} A_v^6(k) \quad (4.12)$$

where N= $2f_s$

7. Steps to determine the variable window width:

(A) To determine starting point k_1 of first peak: compare A_{CLE} to the threshold value '*a*', if it is greater than threshold value, and then marks point as k_1.

(B) To determine ending point k_2 of first peak: compare A_{CLE} from k_1 onwards to the threshold value '*a*', if this value is less, then marks point as k_2.

8. Determine end point '*k*' of current ECG cycle: Select window (k_2:(k_2 + f_s/2)) in enhanced data, determine the standard deviation of enhanced data as follows:

(a) First 8 samples of standard deviation of input data are determined using a variable window of size 8 to 16. Similarly the last 8 samples are determined using a window size of 16 to 8.

(b) The remaining in between samples is obtained by the standard deviation of input data with fixed size of 16. All standard deviation samples are stored in an array, and then the minima of this standard deviation is found, which is the end point '*k'* of current cycle or starting point of next cycle of ECG wave.

9. Detection of QRS: The variable window is mapped in composite lead and filtered data of individual leads and maxima is found with high peak (pki) marked by the symbol (^) as shown in Fig. 4.19 which represents the location of QRS of composite lead. If detected peak is positive, then it is 'R' or otherwise 'S' wave.

10. Adaptive threshold: After first peak detection using threshold 'a' (a = mean (1:2 times f_s)), determine adaptive threshold 'a' (a = mean (enhanced data (end point of current cycle: end point of current cycle + 1.5 times f_s))).

11. From next peak to last peak find starting point k_1 using adaptive threshold 'a', starting from endpoint of previous cycles and following step 7 (A) and for ending point k_2, follow step 7 (B). Skipped period (automatically determined) is used to eliminate false peak detection due to abnormal 'T' wave.

12. All above calculated values are mapped on composite lead and individual leads on each beat as shown in Fig. 4.20.

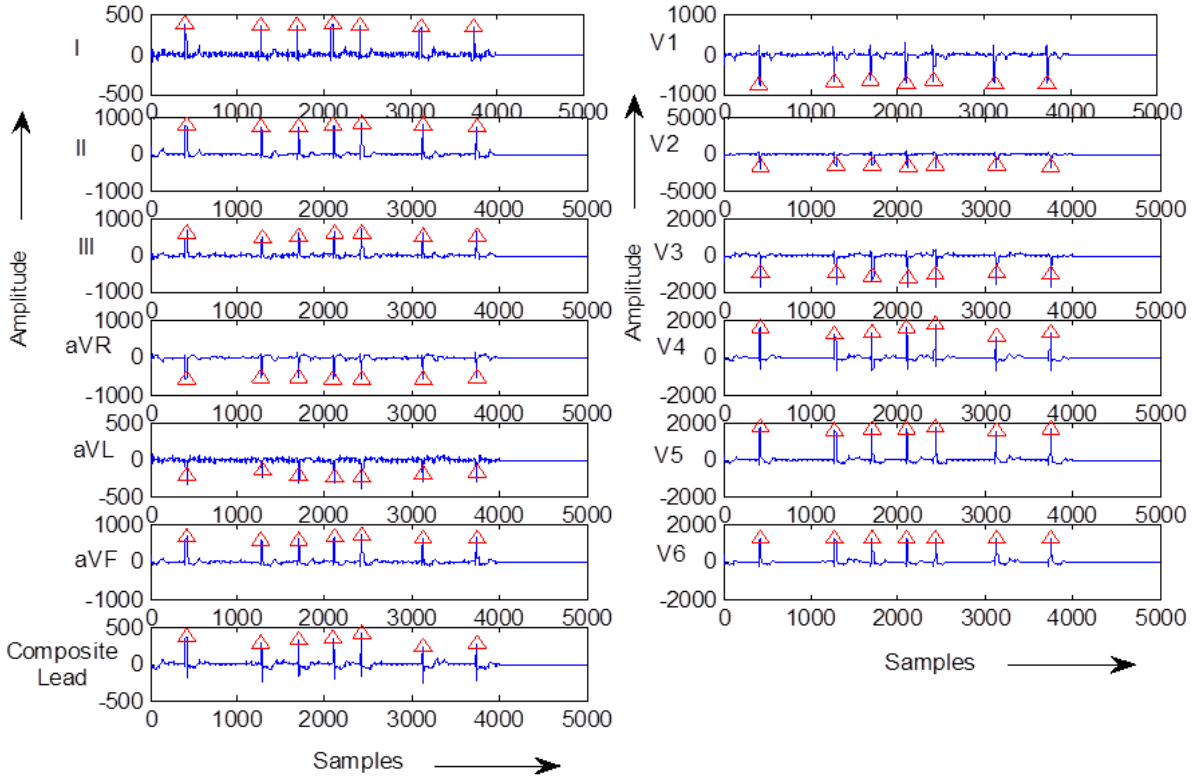

Fig. 4.19 QRS detection and QRS marking by (^) on filtered 12-Lead ECG and composite lead

4.3.3.3 Results and Discussion

The evaluation of this new proposed method is done using standard CSE multilead measurement data set-3, data set-4, PTB database and St.-Petersburg Institute of Cardiological Techniques 12-lead Arrhythmia Database. In order to evaluate the performance of the proposed method, we calculated two parameters, i.e. Sensitivity (Se) and Positive predictivity (+*P*) and performed three experiments with different databases.

Experiment 1

In this experiment, multilead CSE data set-3 and data set-4 are considered and QRS detection is performed in composite lead and in all 12 ECG leads. Fig. 4.20 shows QRS detection in record MO1_002. This record contains power noise and abnormal P & T waves in different leads. The proposed method is able to correctly detect all QRS locations in each of the 12 ECG leads and composite lead. The composite lead consists of all ECG wave components which are normalized, reduced artifacts and other noises and segment parameters are also improved with respect to baseline wander.

Fig. 4.21 depicts the QRS detection in record MA1_012. In this record lead I and aVL contains heavy P-wave that is peaky and noisy, and all leads have baseline drift. In this problem, we observe that composite lead contains less noise than other leads. It is actually enhanced and denoised, so this helps in the determination of all QRS locations clearly in all leads.

Fig. 4.22 shows original CSE record MO2_089, which contains large variation in baseline drift, power noise and large variation in beat intervals. In this problem we observe that composite lead contains less noise than other leads. It is actually enhanced and denoised, so this helps in the determination of all QRS locations clearly in all leads.

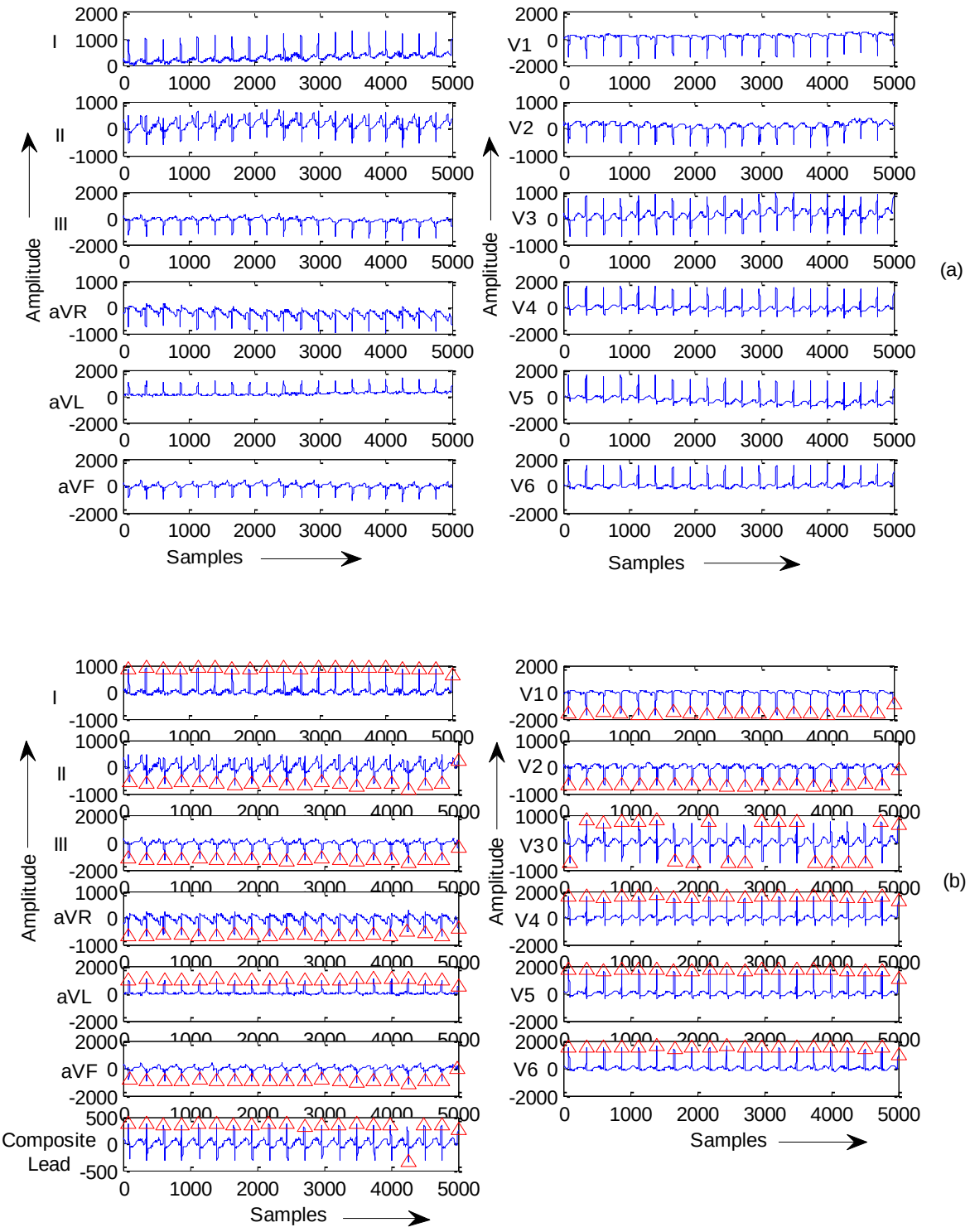

Fig. 4.20 QRS detection of record MO1_002 data (a) Raw 12-Lead ECG data (b) QRS marking by (^) on filtered 12-Lead ECG and composite lead

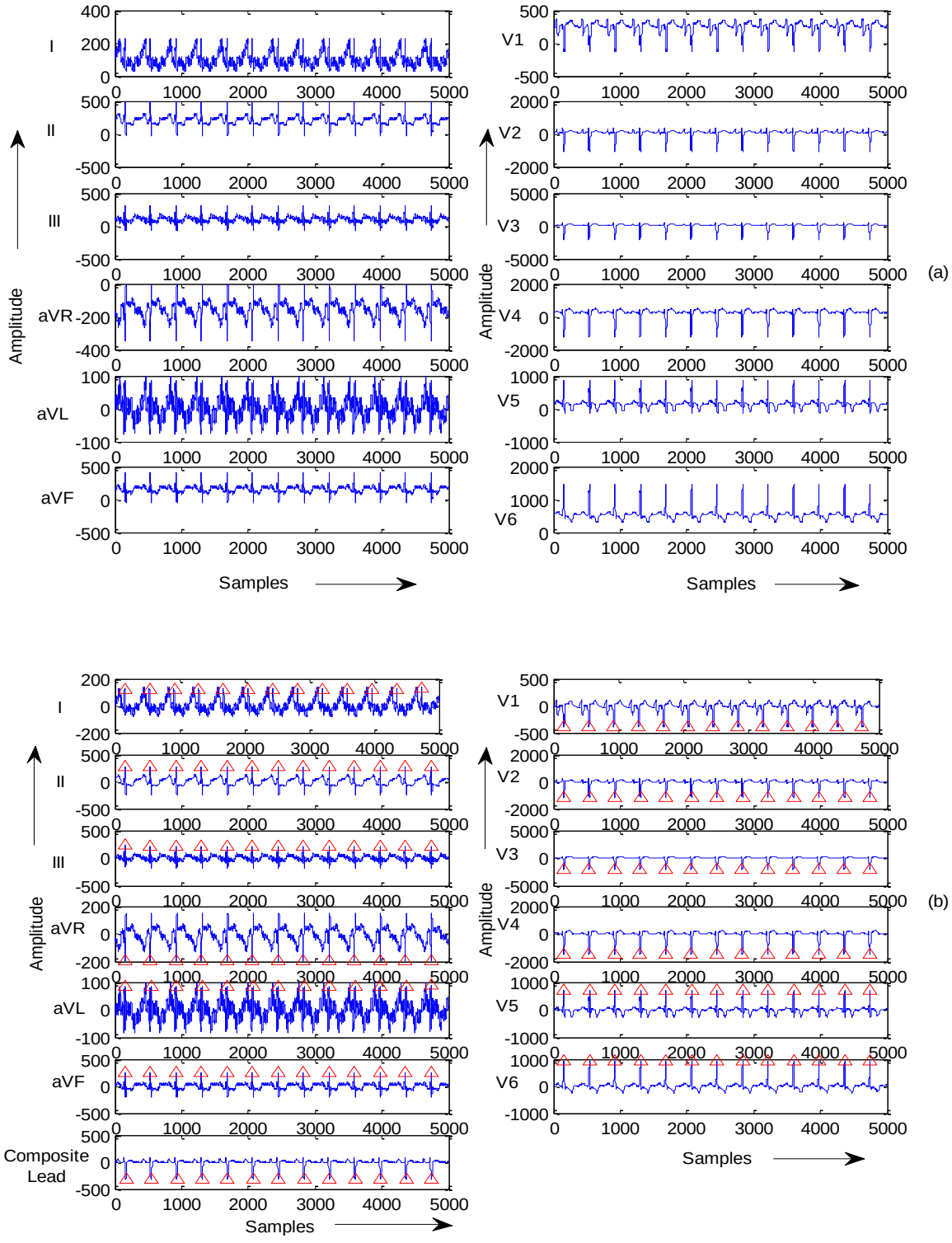

Fig. 4.21 QRS detection of record MA1_012 data (a) Raw 12-Lead ECG data (b) QRS marking by (^) on filtered 12-Lead ECG and composite lead

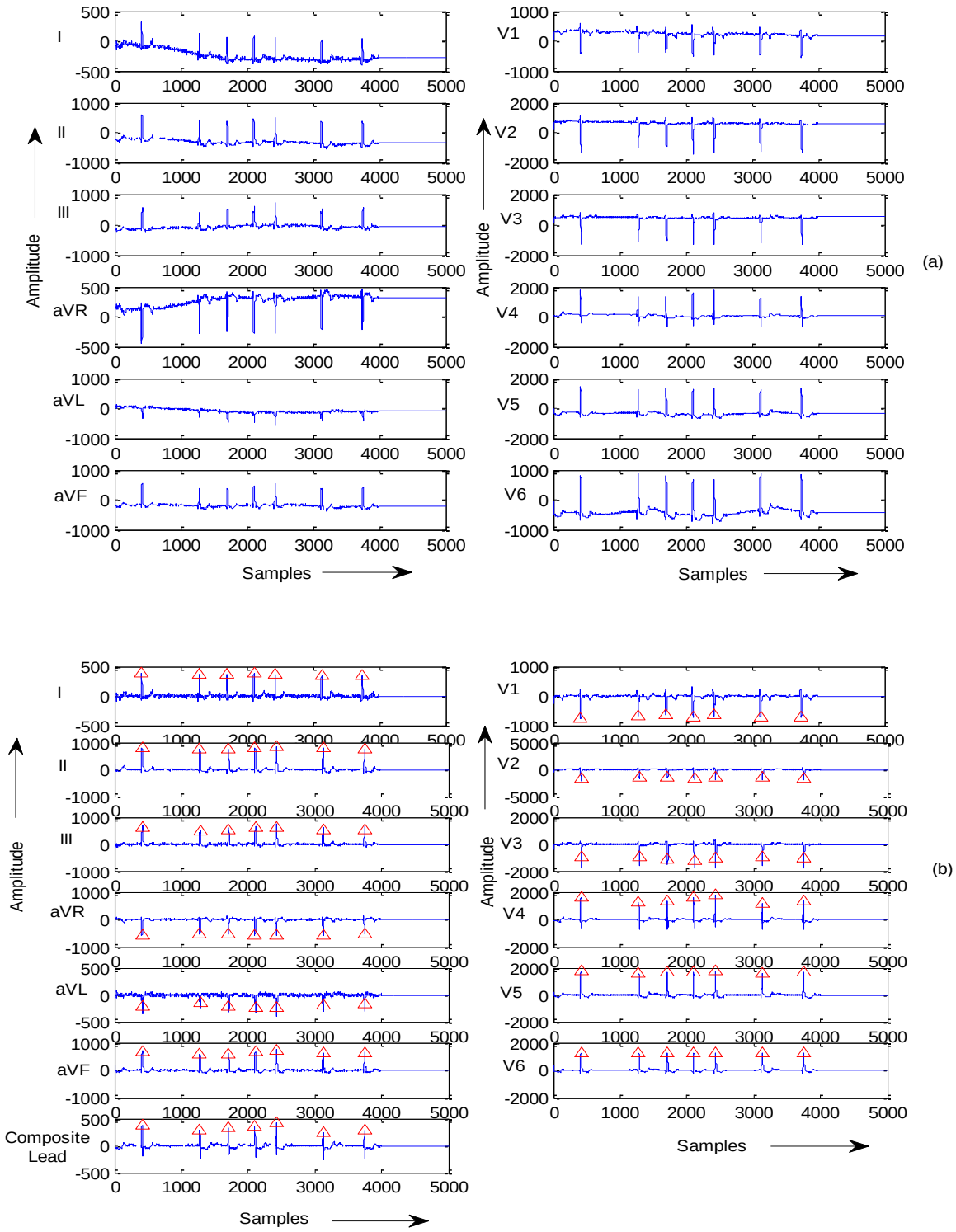

Fig. 4.22 QRS detection of record MO2_089 data (a) Raw 12-Lead ECG data (b) QRS marking by (^) on filtered 12-Lead ECG and composite lead

Evaluation of data set-3 containing original cases 125 (MO1_001 to MO1_125) depicted in Table 4.11. In this evaluation, we observe zero total false positives and two false negatives, resulting in overall QRS detection sensitivity (Se) and positive predictivity (+P) of the original 125 cases (MO1_001 to MO1_125) as 99.86% and 100% respectively. Similarly, data set-3 containing 125 artificial (MA1_001 to MA1_125) cases the proposed method has clearly detected all QRS. In these cases zero false positive and zero false negative have been detected, resulting in overall QRS detection sensitivity (*Se*) and positive predictivity (+*P*) of artificial 125 cases (MA1_001 to MA1_125) as 100% and 100% respectively. Evaluation of data set 4 containing original cases 125 (MO2_001 to MO2_125) is depicted in Table 4.11. In this Evaluation, we observe eight total false positives and three false negatives, resulting in overall QRS detection sensitivity (*Se*) and positive predictivity (+*P*) of the original 125 cases (MO2_001 to MO2_125) as 99.80% and 99.49% respectively. Artificial cases of data set 4 (MA2_001 to MA2_125) are evaluated and given in Table 4.11. In this table, we observe zero false positives and zero false negatives, resulting in overall QRS detection sensitivity (*Se*) and positive predictivity (+*P*) of artificial 125 cases (MA2_001 to MA2_125) as 100% and 100% respectively.

Table 4.11 Summary of QRS detection in CSE multilead measurement complete database (data set-3 & data set-4)

S. No.	Database	Using No. of beats	TP	FP	FN	Se %	+P %
1	CSE data set-3 (MO1_001 to MO1_125)	1498	1496	0	2	99.86	100
2	CSE data set-3 (MA1_001 to MA1_125)	1504	1504	0	0	100	100
3	CSE data set-4 (MO2_001 to MO2_125)	1552	1549	8	3	99.8	99.49
4	CSE data set-4 (MA2_001 to MA2_125)	1584	1584	0	0	100	100
	Total	**6138**	**6133**	**8**	**5**	**99.92**	**99.87**

TP for true positives; FP for false positives and FN for false negative detections.

Experiment 2

In this experiment, multilead PTB database having different diseases and different data length from 32.0 seconds to 120.012 seconds was to be used for QRS detection by a composite load method in all 12 ECG leads. This database contains 549 records from 290 subjects. Each subject is represented by one to five records. Each record includes 15

simultaneously measured signals: the conventional 12 leads (I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, V6) together with the 3 Frank leads (VX, VY, VZ). Each signal is digitized at 1000 samples per second, with 16 bit resolution over a range of ± 16.384 mV. This is diagnostic data containing Healthy controls and different diseases such as Myocardial infarction, Cardiomyopathy/Heart failure, Bundle branch block, Dysrhythmia, Myocardial hypertrophy, Valvular heart disease, and Myocarditis. The QRS detection performance of the proposed method is depicted in Table 4.12, which shows 58 false positives and 2 false negatives, resulting in overall QRS detection sensitivity (Se%) and positive predictivity (+P) of the PTB Database as 99.90% and 100% respectively, for all 12 leads and composite lead.

Table 4.12 Summary of QRS detection in Physikalisch-Technische Bundesanstalt (PTB) complete database

S. No.	PTB Database	Using No. of beats	TP	FP	FN	Se %	+P %
1	P_001 to P_549	73892	73890	58	2	99.90	100

TP for true positives; FP for false positives and FN for false negative detections

Experiment 3

In this experiment, multilead St.-Petersburg Institute of Cardiological Techniques 12-lead Arrhythmia Database was considered and QRS detection in composite lead and all 12 ECG leads in full length was performed. This noisy database contains various diseases such as Acute MI, Transient ischemic attack (angina pectoris), Prior MI, Coronary artery disease with hypertension, Sinus node dysfunction, Supra ventricular ectopy, atrial fibrillation or SVTA, AV block and Bundle branch block. In this database each record is 30 minutes long (4,62,600 samples) and contains 12 standard leads sampled at 257 Hz, with gains varying from 250 to 1100 analog-to-digital converter units per milli volt. This database contains over 1,75,000 beats including approximately 20,000 PVC beats annotations in all. Fig.4.23 depicts record I25 with large wanderbaseline variation with heavy noise with artifacts. In the proposed method, only median filter is applied to remove wanderbaseline and all QRS positions of all 12 leads are determined. In this experiment all 75 records (I01 to I75) were used and QRS detection was performed in all 12 leads and composite lead with variation in QRS morphologies due to large PVCs (over 20,000) in approximate 17,50,000 beats. The QRS detection performance of the proposed method is depicted in Table 4.13, which shows 129 false positive and 8,771 false negative, resulting overall QRS detection sensitivity (Se%) and positive predictivity (+P) of St. Petersburg Institute of Cardiological Techniques 12-lead Arrhythmia Database as 95.86% and 99.91% respectively, for all 12 leads and composite

lead. In this result, thirty data records show sensitivity as 100%, average sensitivity of 40 data records 99.95%, average sensitivity of 50 data records 99.72%, average sensitivity of 60 data records 99.15%, average sensitivity of 70 data records 97.77%, and overall all 75 data records average sensitivity being 95.82%.

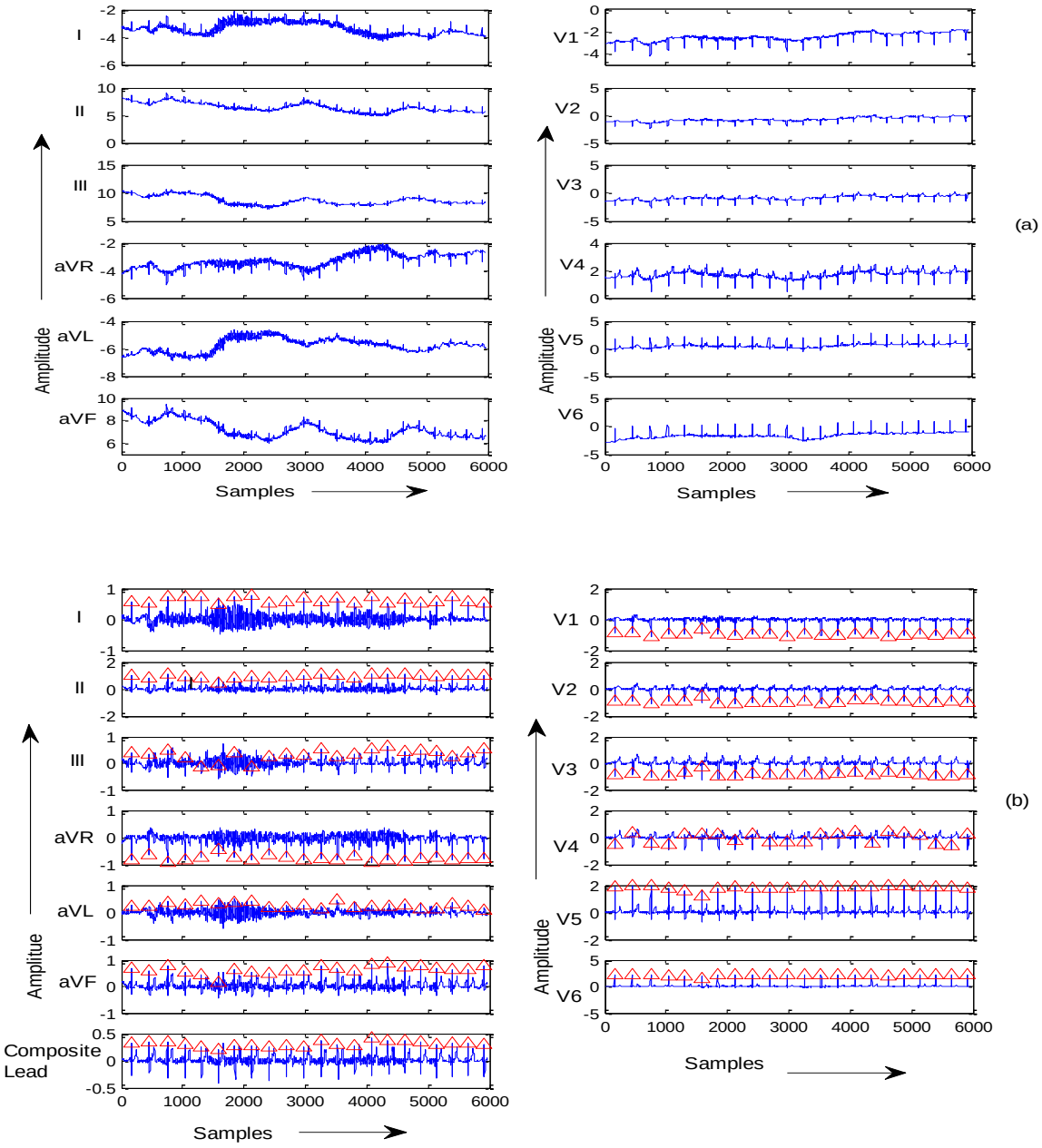

Fig. 4.23 QRS detection of record I25 data (a) Raw 12-Lead ECG data (b) QRS marking by (^) on filtered 12-Lead ECG and composite lead

Table 4.13 Summary of QRS detection in St. Petersburg 12-Lead Arrhythmia full-length (30 minutes long) database

Record Name	Total QRS	TP	FP	FN	Se %	+P %	Record Name	Total QRS	TP	FP	FN	Se %	+P %
I01	2757	2510	0	247	91.04	100.00	I39	1775	1573	0	202	88.62	100.00
I02	2674	2491	0	183	93.16	100.00	I40	2666	2666	1	0	100.00	99.96
I03	2451	2451	5	0	100.00	99.80	I41	1630	1630	1	0	100.00	99.94
I04	2423	2411	0	12	99.50	100.00	I42	3109	2819	0	290	90.67	100.00
I05	1776	1773	0	3	99.83	100.00	I43	2209	2178	0	31	98.60	100.00
I06	2493	2493	1	0	100.00	99.96	I44	2494	2453	0	41	98.36	100.00
I07	2706	2705	0	1	99.96	100.00	I45	1928	1928	2	0	100.00	99.90
I08	2131	2042	0	89	95.82	100.00	I46	2658	2638	0	20	99.25	100.00
I09	2997	2957	0	40	98.67	100.00	I47	1953	1908	0	45	97.70	100.00
I10	3682	3565	0	117	96.82	100.00	I48	2357	2269	0	88	96.27	100.00
I11	2106	2106	3	0	100.00	99.86	I49	2147	2147	2	0	100.00	99.91
I12	2809	2806	0	3	99.89	100.00	I50	2998	2998	2	0	100.00	99.93
I13	2023	2023	1	0	100.00	99.95	I51	2777	2626	0	151	94.56	100.00
I14	1866	1866	3	0	100.00	99.84	I52	1747	1747	3	0	100.00	99.83
I15	2635	2635	5	0	100.00	99.81	I53	2262	2262	0	0	100.00	100.00
I16	1522	1522	5	0	100.00	99.67	I54	2363	2363	25	0	100.00	98.95
I17	1672	1672	3	0	100.00	99.82	I55	2166	2166	2	0	100.00	99.91
I18	3084	2994	0	90	97.08	100.00	I56	1705	1704	0	1	99.94	100.00
I19	2063	2063	3	0	100.00	99.85	I57	2867	2807	0	60	97.91	100.00
I20	2652	2540	0	112	95.78	100.00	I58	2325	2321	0	4	99.83	100.00
I21	2184	2184	3	0	100.00	99.86	I59	2148	2147	0	1	99.95	100.00
I22	3126	2835	0	291	90.69	100.00	I60	2475	2475	2	0	100.00	99.92
I23	2205	2201	0	4	99.82	100.00	I61	1454	1454	4	0	100.00	99.73
I24	2571	2571	2	0	100.00	99.92	I62	2269	2235	0	34	98.50	100.00
I25	1712	1712	25	0	100.00	98.56	I63	1994	1926	0	68	96.59	100.00
I26	1509	1509	9	0	100.00	99.41	I64	1913	1913	2	0	100.00	99.90
I27	2605	1706	0	899	65.49	100.00	I65	2664	2533	0	131	95.08	100.00
I28	1717	1716	0	1	99.94	100.00	I66	2340	2262	0	78	96.67	100.00
I29	2621	1889	0	732	72.07	100.00	I67	2974	2841	0	133	95.53	100.00
I30	2462	1817	0	645	73.80	100.00	I68	2644	2644	10	0	100.00	99.62
I31	3210	1833	0	1377	57.10	100.00	I69	2169	2169	1	0	100.00	99.95
I32	1619	1599	0	20	98.76	100.00	I70	1666	1666	1	0	100.00	99.94
I33	1837	1837	1	0	100.00	99.95	I71	1670	1660	0	10	99.40	100.00
I34	1965	1950	0	15	99.24	100.00	I72	2269	2010	0	259	88.59	100.00
I35	3675	3212	0	463	87.40	100.00	I73	1992	1980	0	12	99.40	100.00
I36	3911	2886	0	1025	73.79	100.00	I74	2404	2389	0	15	99.38	100.00
I37	2461	2461	2	0	100.00	99.92	I75	2103	1812	0	291	86.16	100.00
I38	2699	2257	0	442	83.62	100.00	**Total**	**175895**	**167124**	**129**	**8771**	**95.86**	**99.91**

TP for true positives; FP for false positives and FN for false negative detection

Table 4.14 represents the overall performance of proposed method, using different standard databases, such as CSE, PTB and St-Petersburg multilead Arrhythmia with

different cases and total 2,55,925 beats analysis. The overall average sensitivity of 99.24% and positive predictivity of 99.90% was achieved considering all different standard databases.

Table 4.14 Summary of QRS detection in different multilead ECG database

S. No.	Database	Using No. of beats	TP	FP	FN	Se %	+P %
1	CSE data set-3 (MO1_001 to MO1_125)	1498	1496	0	2	99.86	100
2	CSE data set-3 (MA1_001 to MA1_125)	1504	1504	0	0	100	100
3	CSE data set-4 (MO2_001 to MO2_125)	1552	1549	8	3	99.8	99.49
4	CSE data set-4 (MA2_001 to MA2_125)	1584	1584	0	0	100	100
5	PTB P_001 to P_549	73892	73890	58	2	99.90	100
6	St-Petsberg multilead Arrhythmia I01 to I75	175895	167124	129	8771	95.86	99.91
	Total	**255925**	**247147**	**195**	**8778**	**99.24**	**99.90**

In Multilead QRS detection, researcher Gritzali [83] used three channel data to perform QRS detection in CSE database data set-1 and obtained QRS detection rate 99.87%. Author Saxena et al [21] proposed multilead QRS detector on the basis of single-lead QRS detector and performance evaluated using multilead measurement CSE. Another researcher Mehta et al [82] used twelve channel data using data set-3 (MO1_001-MO1_125) to perform QRS detection with a detection rate of 99.75%. Table 4.15 depicts QRS detection performance by various methods using CSE databases. The proposed algorithm performs QRS detection comparable and higher than other methods for CSE data sets. Proposed method tested on all CSE databases and long length databases like PTB of 540 cases and St. Petersburg Institute of Cardiological Techniques 12-lead Arrhythmia of 75 cases. Multilead QRS detection for long data was not used by any author, so proposed method could be used for multilead ECG analysis.

The new method was implemented by using MATLAB 7.8.0 (2009a) Software in a P. C. with Intel Core 2 Duo 2.67 GHz. The performance of the proposed method is higher or comparable with other methods. The average computational time for QRS detection of the new proposed algorithm is approximately 5.20 to 5.50 seconds for composite lead and 12-Lead ECG records of CSE data set-3 & data set-4. The average computational times for St.-

Petersburg Institute of Cardiological Techniques 12-lead Arrhythmia Database is approximately 8.6 minutes for 30 minutes each 12 lead with a composite lead.

Table 4.15 Comparison of QRS detection with another algorithm using CSE database

S. No.	QRS Detector	Method	Data set	Detection rate %
1	Bemmel et al [23]	Spatial velocity function (3 simul. ECG)	CSE DS1	99.6
		Spatial velocity function (3 simul.VCG)	CSE DS1	99.9
		Spatial velocity function (multi-lead)	CSE DS3	100
2	Gritzali [83]	Length transformation(Three Channel)	CSE DS1	99.87
		Energy transformation(Three Channel)	CSE DS1	99.13
3	Kyrkoy et al [80]	Time recursive prediction technique	CSE DS2	99.00
4	Mehta et al [82]	Support vector machine(Twelve Channel)	CSE DS3	99.75
5		**Proposed method**(Twelve Channel)	CSE DS3 (MO1_001 -125)	99.86
		Proposed method(Twelve Channel)	CSE DS3 (MA1_001 -125)	100.00
		Proposed method(Twelve Channel)	CSE DS4 (MO2_001 -125)	99.80
		Proposed method(Twelve Channel)	CSE DS4 (MA2_001 -125)	100.00

TP for true positives; FP for false positives and FN for false negative detections

4.3.3.4 Conclusions of 12-Lead ECG QRS detection

An effective and reliable multilead QRS detection method based on generation of composite lead using point by point averaging of preprocessed 12 lead ECG signals has been proposed in this work. The proposed methodology effectively reduces the search space for QRS detection by obtaining a variable search window by enhancement of composite lead using the sixth power of a signal. The variable search window is mapped on all the individual ECG leads for QRS detection. The advantage of the proposed methodology is the use of single variable size search window for simultaneous QRS detection on all 12 ECG leads. However, the other related researches have used different thresholds for all 12 ECG leads. This proposed new method was tested on standard CSE multilead measurement complete database, PTB database and St.-Petersburg Institute of Cardiological Techniques 12-lead Arrhythmia Database and obtained good results & statistical indices are higher or

comparable to other related research in the scientific literature. This simple, fast and reliable method for simultaneous detection of QRS locations of composite lead as well as all 12 ECG leads can be used for myocardial infarction and arrhythmia monitoring. The clinical information presented in the composite lead can assist the cardiologist for ECG signal interpretation and analysis, including the clinical distinction of aberrant conduction from ventricular premature complexes.

4.4 Summary

In this chapter, two QRS detection method based on single lead and multilead ECG has been presented.A simple and efficient new method for QRS detection in Electrocardiogram is proposed in this research work. The initial data is preprocessed using two stage median filter for removing baseline drift. The second stage enhances the peaks of ECG wave components by using the sixth power of a signal. The next stage identifies the QRS complex by taking a variable window size. The performance of the new algorithm is evaluated against the standard databases. The detection sensitivity (Se) and positive predictivity (+P) of CSE, MIT/BIH AD, ESC ST-T and QT databases are Se 99.51 &+P 99.69%, Se 99.21&+P 99.34%, Se 99.53&+P 99.72% and Se 99.87&+P 99.95% respectively. These four standard databases (CSE, MIT/BIH AD, ESC ST-T and QT databases) used to perform QRS detection consider 368 cases, tested on 1006168 beats and achieved overall average sensitivity 99.52% and positive predictivity 99.69%. The QRS detection was also performed on 12 datasetsnoisy, full lengths (118e24 to 118e_06 and 119e24 to 119_06) from MIT–BIH Noise Stress Test Database and obtained performance is higher and or comparable to other algorithms in literature.

QRS detection in 12-Lead Electrocardiogram (ECG) using composite lead and peak enhancement method is proposed in this thesis. Initially raw signals of 12-Lead electrocardiogram having sampled frequency f_s are pre-processed for baseline wander removal using a two stage median filter with window widths of $f_s/2$ and f_s respectively. The point by point average of the preprocessed signals corresponding to 12-leads is taken to generate a composite lead. In order to obtain a variable size search window for QRS detection, the composite lead is enhanced by the sixth power of the signal and its mean value is determined. The maximum value of the search space defined by the search window mapped on the composite lead and other 12 ECG leads of 12-lead ECG individually for QRS detection. The performance of the multilead algorithm is evaluated against the CSE multilead measurement database, PTB Database, and St. Petersburg Institute of Cardiological Technic's 12-lead Arrhythmia Database. The overall average sensitivity 99.24% and positive predictivity of 99.90% was achieved considering all different standard multilead databases (CSE, PTB and St-Petersburg multilead Arrhythmia with different cases and total 2,55,925 beats analysis).

The composite lead signal contains similar morphology of P-QRS-T with same interval and duration. The variation is only in amplitudes; hence it is more enhanced lead because it is the resultant of all 12 leads. This lead is suitable for all possible measurements and rhythm analysis. The ECG wave complexes in composite lead are noise free and enhanced in comparison to all 12 leads. The proposed composite lead yields higher sensitivity and positive predictivity on standard benchmark datasets (short and long) which indicate its usefulness for ECG signal to mark & identify various wave components and rhythm analysis in a clinical environment in order to assist cardiologists for different diseases. The both algorithms' have been tested on standard databases and results are very satisfactory.

CHAPTER 5: MULTILEAD ECG ANALYSIS AND FEATURE EXTRACTION

The previous chapter explains the methods of QRS detection for single Lead and 12 Lead ECG signal. The QRS is the main feature of ECG signals, after that detection of other features such as interval, duration, and amplitude for diagnosis purpose are advanced. Therefore, have methodsbeen proposed here in this chapter for boundaries marking in 12 Lead ECG signal, and also calculations of other features in the ECG signal.

5.1 Overview

Cardiologists diagnose heart disorders by analysis of ECG recordings based on their knowledge and expertise. They analyze ECG patterns by determining variations in clinical relevant intervals, amplitudes and polarities of different wave forms such as P-wave, QRS-complex and T wave. Generally, computer analysis, ECG programs consist of two parts: the clinical measurements and diagnostic interpretation. In the computerized ECG analysis, the clinical measurement part, determines the location and reference boundaries of QRS complex, P-wave, and T-wave. Mostly, ECG analysis is based on single lead and multilead signals. In a single lead ECG analysis generally lead II is preferred. In case of multilead ECG analysis, 12 lead at a time (Programs: Marquette, Glasgow and Padova), 6 leads (lead I to aVF and lead V1 toV6) at a time in program Hannover, 3 leads (II, V2 and V6) at a time in Modular program and 15 leads (12 lead ECG and 3 XYZ leads) at a time in Halifax program are used.Some programs (HP, IBM, NAGOYA and Telemed) select groups of leads at a time, such as lead group I-III, aVR-aVF, V1-V3, V4-V6 [40].

There are various automatic ECG analysis and interpretation programs developed by researchers in the last six decades based on different approaches. These are spatial velocity function [2, 4-7, 8, 9, 20], differentiation [3], template-matching [10-11]. Derivative based [22], Wavelet based [49, 77, 78]. In the multilead ECG analysis, the simultaneous leads are transformed into a detection function. The transformation of ECG signal brings out only QRS complexes amongst the other signal, and increase QRS detection rate. Generally, transformation is used in spatial velocity functions for VCG or 12-lead ECG. Mostly, the spatial velocity function has been computed by combining the derivatives of all VCG or ECG leads. Once a spatial velocity function of the QRS complex is detected, after that, most algorithms apply further rules for QRS complex detection. In the derivative and differentiation based algorithms determination of boundary marking assuming a noise free by removing low pass or high pass filter. Similarly, in wavelet transform a preselected frequency band is assumed in which QRS complexes or other ECG wave component energies exist using a combination of low and high pass filter. In wavelet transform method QRS complex energies decrease, if the scale is larger than 2^4 and the energies of artifacts increase for scales greater than 2^5 [49]. In wavelet based methods there are no general rules for selecting a

wavelet for a particular application [50]. Selection criteria of wavelet for a particular application depend on trial method. In wavelet methods, fringing effects occur at both the ends of the signal and phase shift problems also occur. So in order to overcome these effects some operations are needed. Methods based on ANN and SVM require exhaustive training, settings and estimation of model parameters. Most of these techniques for QRS detection are computationally complex because of using more preprocessing steps.

In the literature, other several boundaries marking methods working on the single or multilead system are compared with annotations marked by cardiologists [40, 153]. However, the marking of boundaries is sometimes a difficult task for expert cardiologist, particularly onset-offset from P-wave and the end of the T-wave. In the manual measurementof QT intervals, in case of missing ECG wave components in lead II, the referees were instructed to mark the T-wave end in other waves [153]. In the CSE pilot study different methods are used by researchers for various VCG and ECG programs. In the CSE study, referees analyzed ECG with modified protocol and used every fifth case of the selected beats from artificial library. The referees marked *onsets* and *offsets* of P wave, QRS complex and *end* of T wave. In this process referees received noise free (50 or 60 Hz interference filtered) and an enlarged copy of all leads, after that they marked boundaries with the help of translucent ruler using same beat position in all leads. These measurements again review and then final considered [40]. Actually, in my opinion, this phenomenon is called a visual average concept. The same concept, I used for manually boundary marking in multilead ECG by obtaining composite (average) lead and, also used in automatic boundary marking. This composite lead similar to other leads and more enhanced in wave complexes such as P, QRS and T waves.

5.2 Multilead ECG Analysis Method

In the proposed method, I have designed composite signal based on average of the 12 lead ECG signal. In this method, I create a new signal from the combination of all 12 lead ECG. This signal is more suitable for visual analysis and automatic boundaries marking in multilead ECG signal, because averaging of 12 lead ECG reduces noise times and composite signal is more enhanced than other 12 lead ECG signals [152]. Fig. 5.1 depicted 12-Lead ECG data signals with different noises and composite Lead.

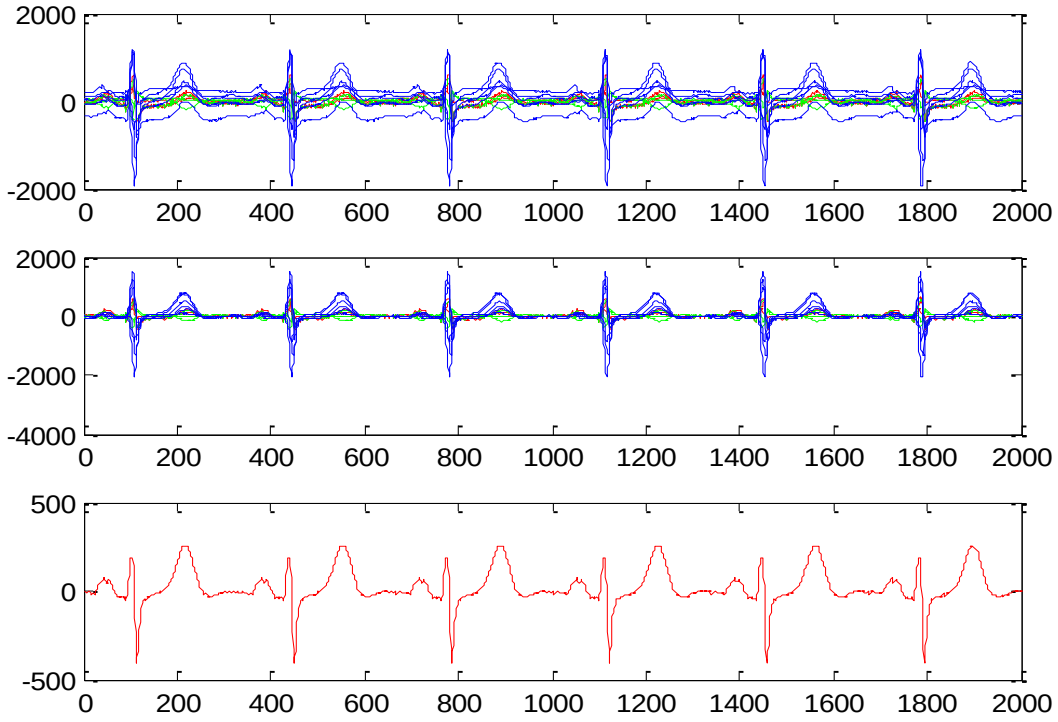

Fig. 5.1 Top to bottom (a) Raw 12 lead ECG signal, (b) Baseline wander free signal (c) Composite lead signal

In the present work, an enhanced composite ECG lead is used for detection of ECG wave components and boundaries marking of all ECG wave components. Therefore, I used composite lead for QRS detection and measurement of boundaries of ECG signals. This study proposes a simple and reliable method for QRS detection in the 12-Lead simultaneously recorded ECG data. In this method raw ECG data are pre-processed with two stage median filters for removing base line drift of signals and added. Then all 12-Lead ECG data are averaged at each point and a composite lead signal is obtained by arranging all averaged values in an array. This composite lead is more enhanced in P wave, QRS complex and T wave region, minimizing power noise, high frequency noise, including high peak abnormality of P and T waves as depicted in Fig. 5.1. After that QRS complex of composite lead signal is enhanced, using the sixth power of composite signal that intensifies the signal strength more as compared to noise and artifacts including P and T-waves [151]. This method does not need any filter to remove P and T-waves. The average value of higher power composite signal is changed and attained some threshold level to discriminate amplitude of QRS complex from artifacts and, P & T-waves. This method is simple in computation, efficient and detects QRS in all 12 leads in 12 Lead ECG systems using single threshold. So here I observe that there is no requirement of threshold for each lead. This method determined variable window mapped on selected point and determined exact QRS locations in specified section without any more processing. After detection of QRS location in

composite lead signal, other clinical wave components such as P and T-waves locations and their boundaries are determined using standard deviation concepts.

A schematic block diagram of the proposed method for ECG wave components detection and boundary marking in 12-Lead ECG systems is depicted in Fig. 5.2 which consists of two stage median filters, composite lead generation, Enhancement of composite lead, determination of variable window size by using the mean of enhanced composite lead and determines the location of high peak value in the complex region.

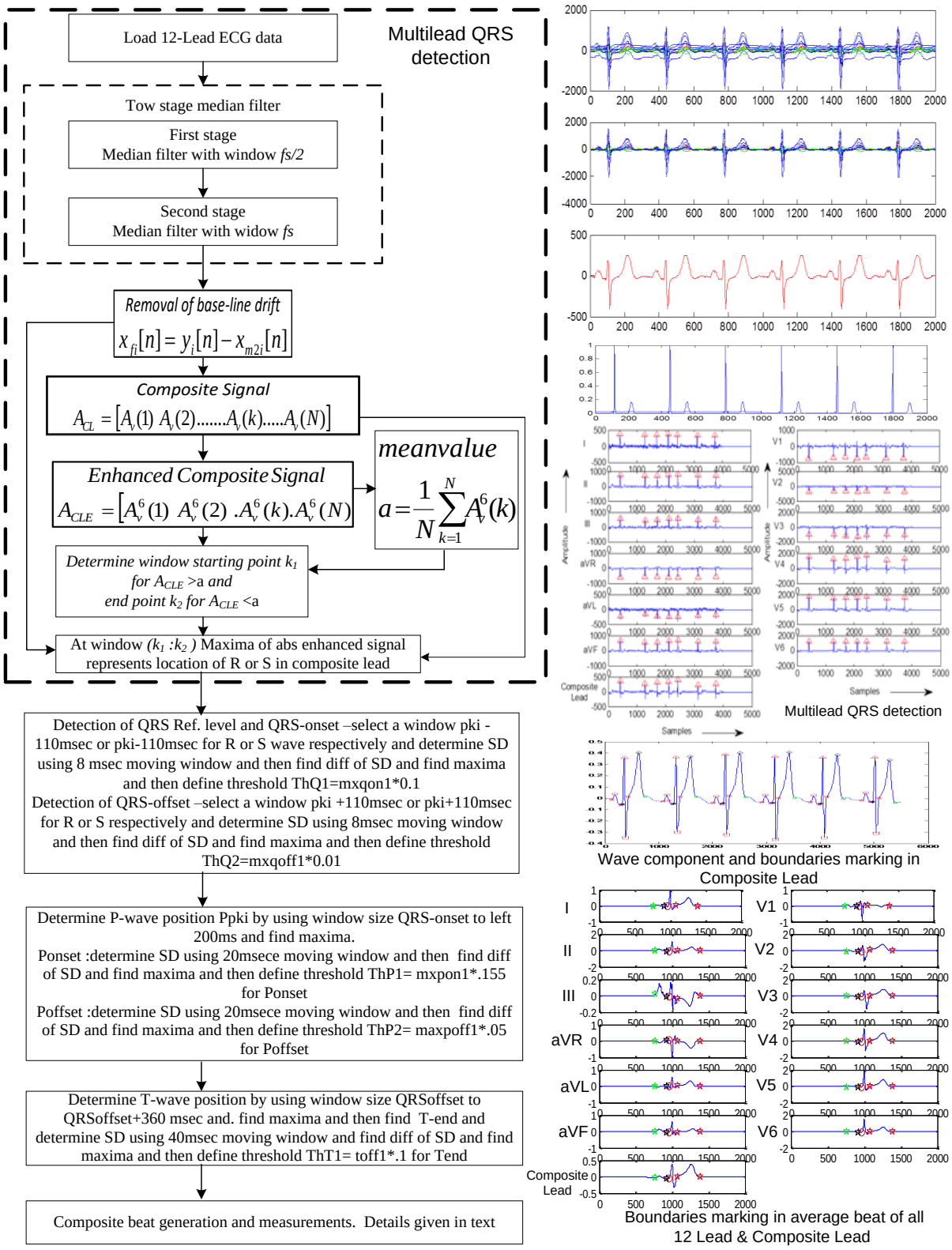

Fig. 5.2 Schematic diagram for QRS detection and boundaries marking in 12-lead ECG

5.2.1 Steps for wave components detection and boundary marking

The QRS detection, detailed steps are described as follows:

1. Load 12-Lead ECG data, having sampled frequency f_s and number of total samples N of each data given by

$$\begin{bmatrix} y_1[n] \\ - \\ y_i[n] \\ - \\ y_{12}[n] \end{bmatrix} = \begin{bmatrix} x_{1,1}[n] & x_{1,k}[n] & x_{1,N}[n] \\ - & - & \\ x_{i,1}[n] & x_{i,k}[n] & x_{i,N}[n] \\ - & - & \\ x_{12,1}[n] & x_{12,k}[n] & x_{12,N}[n] \end{bmatrix} \quad (5.1)$$

Where $y_1[n], y_2[n]. \ . \ , y_{12}[n]$ represent 12-Lead ECG data and $x_{1,1}[n]$, .., $x_{1,N}[n]$ represent respective data values.

2. Select a channel of ECG data say $y_i[n]$.
3. Apply two stage median filter to remove baseline drift

(A) First stage median filter: using window width $f_s/2$

(a) Input data $y_i[n]$ having total samples 'N' and sampling frequency f_s

(b) In this stage median value of the input data $y_i[n]$ to be determined and stored in an array $x_{m1i}[n]$ from 1 to $f_s/4$ points using a variable window size from $f_s/4$ to $f_s/2$ by increasing one by one sample.

(c) In next stage median values of input data $y_i[n]$ to be determined and stored in an array $x_{m1i}[n]$ from $f_s/4+1$ to $N-f_s/4$ points using a moving window size $f_s/2$.

(d) In last stage median values of input data $y_i[n]$ to be determined and stored in an array $x_{m1i}[n]$ from $N-f_s/4+1$ to N points, using a variable window size from $f_s/2$ to $f_s/4$.

(B) Second stage median filter:-using window width f_s

(a) Take first stage data $x_{m1i}[n]$ having total samples 'N'.

(b) In this stage median value of data $x_{m1i}[n]$ to be determined and stored in an array $x_{m2i}[n]$ from 1 to $f_s/2$ points using a variable window size of $f_s/2$ to f_s.

(c) In next stage median values of data $x_{m1i}[n]$ to be determined and stored in an array $x_{m2i}[n]$ from $f_s/2+1$ to $N-f_s/2$ points using a moving window size f_s.

(d) In last stage median values of input data $x_{m1i}[n]$ to be determined and stored in an array $x_{m2i}[n]$ from $N-f_s/2+1$ to N points using a variable window size of f_s to $f_s/2$.

(e) To remove baseline drift from signal $x_{fi}[n]$ subtract second stage median filter output $x_{m2i}[n]$ from input data $y_i[n]$.

$$x_{fi}[n] = y_i[n] - x_{m2i}[n] \tag{5.2}$$

Similarly find other remaining lead data. All 12-Lead ECG filtered data obtained calculated composite lead data.

4. Generation of composite (complex) lead data:

(a) All 12-Lead ECG filtered data are given by

$$\begin{bmatrix} x_{f1}[n] \\ . \\ x_{fi}[n] \\ . \\ x_{f12}[n] \end{bmatrix} = \begin{bmatrix} x_{f1,1}[n] & & x_{f1,k}[n]...x_{f1,N}[n] \\ . & . & . \quad ... \\ x_{fi,1}[n] & & x_{fi,k}[n]...x_{fi,N}[n] \\ . & . & . \quad ... \\ x_{f12,1}[n] & & x_{f12,k}[n]...x_{f12,N}[n] \end{bmatrix} \tag{5.3}$$

(b) To determine the simultaneous space average $A_v(k)$ of the composite (complex) lead signal taking average of all lead data at each sample position and take the simultaneous space average value $A_v(k)$ of all lead data at k^{th} position given by

$$A_v(k) = \frac{1}{12}\left[\sum_{i=1}^{12} x_{fi,k}[n]\right] \tag{5.4}$$

Composite (complex) lead signal A_{CL} given by

$$A_{CL} = \left[A_v(1)\ A_v(2)\ ..A_v(k)..A_v(N)\right] \tag{5.5}$$

This composite lead signal is similar to other 12-Lead ECG system and consists of all complexes such as P, QRS and T waves. In this signal QRS complex region more enhanced than P and T waves in other 12-Leads ECG system. P and T wave region also smoothed. Composite Lead wave form and morphology is approximately same as other 12-Leads.

5. Again enhancement of various peaks such as P, QRS, T waves is done by taking the sixth power of composite signals A_{CL}. The enhanced composite signal A_{CLE} is given by

$$A_{CLE} = \left[A_v^6(1)\ A_v^6(2)\ ..A_v^6(k)..A_v^6(N)\right] \quad (5.6)$$

6. Mean value **'***a***'** of enhanced composite signal A_{CLE} of length 1 to $2f_s$ is given by

$$a = \frac{1}{N}\sum_{k=1}^{N} A_v^6(k) \quad (5.7)$$

where N= $2f_s$

7. Steps to determine the variable window width:

(A) To determine starting point k_1 of first peak: compare A_{CLE} to the threshold value **'***a***'**, if it is greater than threshold value, and then marks point as k_1.

(B) To determine ending point k_2 of first peak: compare A_{CLE} from k_1 onwards to the threshold value **'***a***'**, if this value is less, then marks point as k_2.

8. Determine end point '*k*' of current ECG cycle: Select window (k_2:(k_2 + f_s/2)) in enhanced data, determine the standard deviation of enhanced data as follows:

(a) First 8 samples of standard deviation of input data are determined using a variable window of size 8 to 16. Similarly the last 8 samples are determined using a window size of 16 to 8.

(b) The remaining in between samples is obtained by the standard deviation of input data with fixed size of 16. All standard deviation samples are stored in an array, and then the minima of this standard deviation is found, which is the end point '*k'* of current cycle or starting point of the next cycle of ECG wave.

9. Detection of QRS: The variable window is mapped in composite lead and filtered data of individual leads and maxima is found with high peak (pki) marked by the symbol (^) as shown in Fig. 5.3 which represents the location of QRS of composite lead. If detected peak is positive, then it is 'R' or otherwise 'S' wave.

(a) *Detection of QRS Reference level or* QRS_{onset}: Select a window size pki-110 ms to pki or pki-120 ms to pki in the composite lead for R or S wave respectively, and determine standard deviation using 8 msec moving window and then find difference of standard deviation and find maxima (mxqon1). Then define threshold ThQ1=mxqon1*0.1 or ThQ1=mxqon1*0.06 for R or S respectively, and find QRS_{onset} in specified standard deviation differences crossing threshold ThQ1.

(b) *Detection of* QRS_{offset}: Select a window pki:pki+120 ms or pki:pki+110 ms for R or S respectively, and determine standard deviation using 8 ms moving window and then find differences of standard deviation and find maxima (mxqoff1) and then define threshold ThQ2=mxqoff1*0.01 or ThQ2=mxqoff1*0.1 for R or S

respectively and find QRS_{offset} in specified standard deviation differences crossing threshold ThQ2.

10. *Detection of P-wave location and onset-offset:* Determine P-wave position (Ppki) by using window size QRS_{onset} to left 200 ms and find absolute maxima (Ppki).
    (a) P_{onset}: Select a window Ppki:Ppki-110 ms, determine standard deviation using 20 ms moving window and then find differences of standard deviation and find maxima (mxpon1) and then define threshold ThP1= mxpon1*0.155 and find P_{onset}in specified standard deviation differences crossing threshold ThP1.
    (b) P_{offset}: Select a window Ppki:Ppki+110 ms, determine standard deviation using 20 ms moving window and then find differences of standard deviation and find maxima (mxpoff1) and then define threshold ThP2= mxpoff1*. 05 and find P_{offset} in specified standard deviation differences crossing threshold ThP2.
11. *Detection of T-wave location and T-end*: Determine T-wave position by using window size QRS_{offset} to QRS_{offset}+360 msec and find absolute maxima (Tpki)

    To determine T_{end} : Select window size Tpki:Tpki+180 ms, determine standard deviation using 40 ms moving window, find difference of standard deviation, find maxima (toff1), define threshold ThT1= toff1*.1 and then comparethreshold THT1 with standard deviation difference and find T_{end}.
12. *Adaptive threshold:* After first peak detection using threshold 'a' (a = mean (1:2 times f_s)), determine adaptive threshold 'a' (a = mean (enhanced data (end point of current cycle: end point of current cycle + 1.5 times f_s))).
13. From next peak to last peak find starting point k_1 using adaptive threshold 'a', starting from endpoint of previous cycles and following step 7 (A) and for ending point k_2, follow step 7 (B). Skipped period (automatically determined) is used to eliminate false peak detection due to abnormal 'T' wave. All above calculated values such as peaks and boundaries are mapped on composite lead and on each beat as shown in Fig. 5.3.

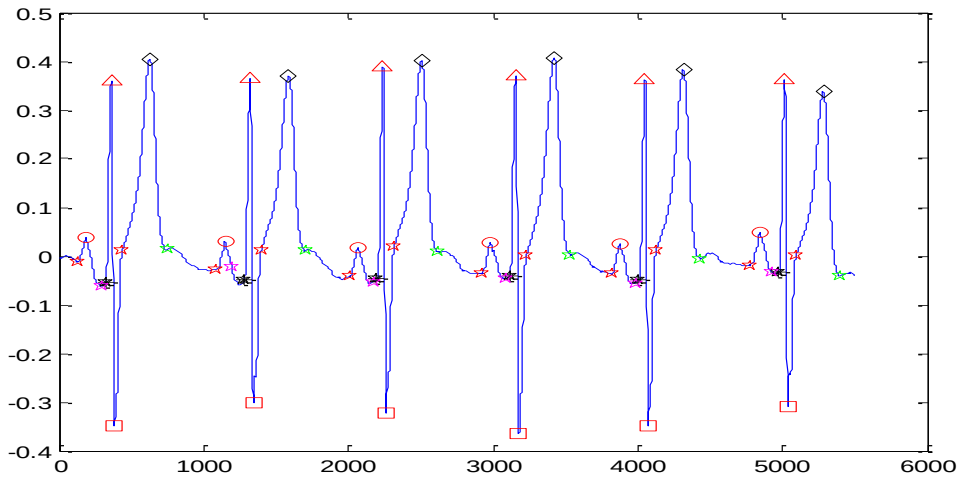

Fig. 5.3 Peaks and boundaries (*p_{onset} &P_{offset} *QRS_{onset}& QRS_{offset} *T_{end}, ⬭ P-Peak △ R_{peak} ▢ S_{peak} and ◇T_{peak}) marking in composite signal

5.2.2 Results and Discussion

This section explainsthe results of five wave boundaries such as P_{onset}, P_{offset}, QRS_{onset}, QRS_{offset}, and T_{end} with the developed software. To validate developed software, CSE data set-3 was used. In the CSE study a data set-3 of 125 electrocardiogramswith selected abnormalities was analyzed by a group of five referee cardiologists and twenty (thirteen different 12 lead and seven XYZ lead) computer programs as mentioned in CSE result. In CSE data set-3, five referee group evaluated 25 records such as record number 1, 6, 11, 16, 21, 26, 31, 36, 41, 46, 51, 56, 61, 66, 71, 76, 81, 86, 91. 96. 101, 106, 111, 116, and 121 for estimation of five wave boundaries (P_{onset}, P_{offset}, QRS_{onset}, QRS_{offset}, and T_{end}). Table 5.1 depicts the results of developed software and referee median results. The results evaluation has been performed in terms of differences of mean and standard deviation in referee values and developed a program [40]. For P_{onset} and P_{offset} analysis, mean differences are calculated and mean error is determined as -4.28 and 1.4 with the standard deviation values equal to 4.42 and 6.02 respectively. Similarly, for QRS_{onset}, QRS_{offset}, and T_{end} mean error values are 1.2, -0.76 & -1.92 and standard deviation values being 2.5, 4.30 and 11.39 respectively. In this software we obtained unbiased measurement within specified limits.

Also, compared performance of developing program verses and CSE study developed different twenty programs (thirteen ECG programs and seven VCG programs) with mean and standard deviation differences with respect mean of referee and mean of twenty programs. The comparative performance of developing a program depicted in Table 5.2 and Table 5.3 which shows the performance of boundaries marking higher and comparable to standard CSE developed programs.

Table 5.1 Boundary marking of CSE multilead dataset-3

		P-onset			P-offset			QRS-onset			QRS-offset			T-end		
S. No.	**Record No.**	**RE**	**ME**	**ME-RE**	**RE**	**ME**	**ME-RE**	**RE**	**ME**	**ME-RE**	**RE**	**ME**	**ME-RE**	**RE**	**ME**	**ME-RE**
1	1	22	19	-3	87	90	3	139	139	0	202	205	3	370	371	1
2	6	22	19	-3	74	76	2	87	87	0	129	130	1	270	269	-1
3	11	22	18	-4	77	82	5	97	95	-2	145	145	0	281	290	9
4	16	35	32	-3	86	84	-2	102	99	-3	144	144	0	283	289	6
5	21	105	96	-9	164	172	8	181	180	-1	233	236	3	420	421	1
6	26	40	39	-1	99	104	5	141	143	2	225	227	2	365	367	2
7	31	38	33	-5	100	105	5	124	129	5	173	170	-3	311	318	7
8	36	53	49	-4	106	108	2	124	120	-4	185	183	-2	320	325	5
9	41	56	49	-7	106	93	-13	127	128	1	193	181	-12	340	350	10
10	46	26	33	7	80	70	-10	104	105	1	172	174	2	340	330	-10
11	51	13	9	-4	68	70	2	90	89	-1	135	136	1	246	228	-18
12	56	77	77	0	132	138	6	170	168	-2	218	219	1	391	406	15
13	61	53	56	3	123	126	3	165	168	3	210	207	-3	366	372	6
14	66	63	52	-11	120	120	0	137	140	3	190	188	-2	353	340	-13
15	71	44	36	-8	97	97	0	119	116	-3	161	163	2	302	298	-4
16	76	35	27	-8	99	88	-11	124	122	-2	199	190	-9	320	327	7
17	81	40	35	-5	100	105	5	122	121	-1	180	179	-1	326	327	1
18	86	38	25	-13	94	104	10	120	121	1	186	189	3	370	376	6
19	91	36	25	-11	96	99	3	116	119	3	175	171	-4	331	312	-19
20	96	21	18	-3	79	77	-2	142	144	2	201	196	-5	340	352	12
21	101	24	18	-6	76	85	9	93	91	-2	134	135	1	268	239	-29
22	106	65	63	-2	120	124	4	130	133	3	177	176	-1	346	353	7
23	111	..	51	0	….	93	0	96	100	4	145	138	-7	245	180	-65
24	116	50	46	-4	109	116	7	120	119	-1	163	166	3	314	322	8
25	121	25	22	-3	85	79	-6	124	121	-3	182	190	8	325	333	8
	Mean			**-4.28**			**1.4**			**0.12**			**-0.76**			**-1.92**
	SD			**4.42**			**6.0208**			**2.5053**			**4.3039**			**11.398**
	Reference limit in samples			**6**			**6**			**4**			**6**			**15**

Note: All measurements in samples

RE: CSE reference value, ME: program measure value, ME-RE: difference between measure value and reference value, SD: standard deviation

Table 5.2 Comparison of boundaries performances of ME-REcse with CSE study programs for 25 cases

ECG	P_{onset}		P_{offset}		QRS_{onset}		QRS_{offset}		T_{end}	
Programs	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
	Mean diffR	Std diffR	Mean diffR	Std diffR	Mean diffR	Std diffR	Mean diffR	Std diffR	Mean diffR	Std diffR
ECG1	-20.92	15.81	-16.40	1.04	-6.54	-9.03	-11.46	-1.19	-40.38	-3.15
ECG2	-10.54	9.60	-8.40	-2.47	-1.15	-11.14	-6.54	-1.46	-21.23	-8.37
ECG3	-6.08	6.37	-5.36	-1.36	1.31	-11.75	-5.31	-1.48	-17.00	-8.09
ECG4	-3.58	5.53	-2.20	-1.40	3.08	-11.50	-4.08	-1.04	-14.00	-7.83
ECG5	-1.67	6.20	-0.48	-1.07	4.31	-11.54	-2.69	-1.13	-27.62	51.25
ECG6	-0.17	5.75	1.36	0.01	5.46	-11.25	-1.31	-0.81	-6.85	-6.62
ECG7	1.58	5.44	3.56	2.49	6.31	-11.24	-0.08	-0.31	-4.46	-7.36
ECG8	4.33	11.17	5.44	3.12	7.31	-11.08	2.46	1.52	-23.08	49.58
ECG9	8.58	26.58	4.50	-0.98	8.08	-11.24	4.38	1.58	1.69	-6.40
ECG10	6.52	5.47	6.58	-0.41	8.77	-11.47	6.08	0.89	5.15	-5.18
ECG11	8.96	6.55	12.33	7.51	10.23	-11.27	9.46	1.75	11.20	-5.63
ECG12	17.05	12.60	22.36	20.52	12.31	-11.20	17.69	3.98	27.30	-6.53
ECG13	-10.96	15.84	-6.83	2.78	1.92	-11.74	-6.08	-1.13	-0.04	5.66
VCG1	-6.00	15.58	-14.24	11.61	4.92	-11.07	-3.46	-0.46	-19.85	-4.17
VCG2	-2.42	12.51	-7.96	1.57	7.08	-11.10	-1.54	-0.37	-15.23	-5.80
VCG3	1.17	7.32	-3.44	-2.87	8.08	-10.96	-0.46	-0.23	-10.62	-6.84
VCG4	5.33	6.12	1.04	1.94	10.00	-11.05	1.00	0.53	-5.69	-5.68
VCG5	8.00	4.49	0.61	-1.95	12.00	-11.05	5.08	1.99	3.92	4.80
VCG6	15.45	14.42	5.00	-1.34	13.23	-10.68	10.38	4.77	-3.38	61.31
VCG7	*	*	*	*	*	*	*	*	*	*
Pro-ECG	**-8.56**	**9.21**	**2.8**	**12.04**	**0.24**	**5.01**	**-1.52**	**8.60**	**-3.84**	**22.78**
Tol.Limit		**12ms**		**12ms**		**8ms**		**12ms**		**30ms**

Note: -ECG1 to ECG13 and VCG1 to VCG7 are Programs developed by CSE, Pro-ECG program developed by the author. All measurements are in milli seconds (ms).

Mean diffR: differences between the mean value of 25 CSE reference data measured by ECG1-13, VCG1-7, and Pro-ECG program and mean value of 25 reference data measured by referees

Std diffP: differences between the standard deviation value of 25 CSE reference data measured by ECG1-13, VCG1-7, & Pro-ECG program and standard deviation value of of 25 reference data measured by referees

.

Table 5.3 Comparison of boundaries performances of CSE study programs with developed program for 25 CSE reference records

ECG	P_{onset}		P_{offset}		QRS_{onset}		QRS_{offset}		T_{end}	
Programs	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
	Mean diffP	Std diffP	Mean diffP	Std diffP	Mean diffP	Std diffP	Mean diffP	Std diffP	Mean diffP	Std diffP
ECG1	-22	11	-15	-6	-13	2	-10	0	-23	-22
ECG2	-12	4	-7	-1	-7	0	-6	-1	-4	-27
ECG3	-7	1	-4	-9	-5	-1	-4	-1	0	-27
ECG4	-5	0	-1	1	-3	0	-3	0	3	-26
ECG5	-3	1	1	-8	-2	0	-2	0	-11	33
ECG6	-1	1	2	2	-1	0	0	0	10	-25
ECG7	0	0	5	-5	0	0	1	0	13	-26
ECG8	3	6	6	5	1	0	3	2	-6	31
ECG9	7	21	6	-8	2	0	5	2	19	-25
ECG10	5	0	8	2	3	0	7	2	22	-24
ECG11	8	1	13	0	4	0	10	3	28	-24
ECG12	16	7	23	22	6	0	19	5	44	-25
ECG13	-12	11	-16	-5	-4	-1	-5	0	-23	-13
VCG1	-7	10	-13	14	-1	0	-2	0	-3	-23
VCG2	-4	7	-7	-6	1	0	-1	0	2	-24
VCG3	0	2	-2	-1	2	0	1	1	6	-25
VCG4	4	1	2	-5	4	0	2	1	11	-24
VCG5	7	-1	2	0	6	0	6	3	21	-14
VCG6	14	9	6	-9	7	0	11	6	14	43
VCG7	*	*	*	*	*	*	*	*	*	*
Pro-ECG	-8.56	9.21	2.8	12.04	0.24	5.01	-1.52	8.60	-3.84	22.78
Tol. Limit		**12ms**		**12ms**		**8ms**		**12ms**		**30ms**

Note: -ECG1 to ECG13 and VCG1 to VCG7 are Programs developed by CSE, Pro-ECG program developed by the author. All measurements are in milli seconds (ms).

Mean diffP: differences between the mean value of 25 CSE reference data measured by ECG1-1, VCG1-7, and Pro-ECG program and mean value of twenty standard programs (ECG1 to ECG13 and VCG1 to VCG) developed by CSE.

Std diffP: differences between the standard deviation value of 25 CSE reference data measured by ECG1-13, VCG1-7, & Pro-ECG program and standard deviation value of twenty standard programs (ECG1 to ECG13 and VCG1 to VCG) developed by CSE.

5.3 Feature Extraction

Feature extraction is an important part in automated ECG analysis and classification of particular diseases. At rest ECG analysis cardiologists used particular beat manual measurements and, analysis with averaging concepts. Similarly, automated ECG analysis program measured features used in the rest ECG in particular beat. The main task in the ECG analysis is to find the exact location of the major reference points such as onsets and offsets of P, QRS, and T waves. In the proposed method, for automatic measurement of features like amplitudes, durations of wave segments and intervals and determination of parameters such as area, mean, standard deviation, skewness, and kurtosis, composite beats are used; detailed steps of the method being shown in the following sections.

5.3.1 Composite Beat (Average beat) Generation

In the automatic ECG analysis and diagnosis, system measurement of a dominant beat is required for measurements and interpretation. In this method, initially QRS detection performed in composite lead and all 12-Lead ECG as discussed in previous chapter 4 and after that and boundary marking is performed in Composite lead as discussed in section 5.2 in this chapter. An average beat of composite lead and all 12 lead of 12-Lead ECGs are determined in 10 seconds. All beats are aligned at the high peak pike position as a center location and each beat P_{on} -100 ms to T_{end} +100 ms in 2000 ms window size is considered and then average beat of composite lead is determined. The onsets of P, QRS and offsets of P, QRS and T wave are detected on the average beat of composite lead using boundary making procedure in section 5.2 and these boundaries marking mapped on all 12 lead ECGs. The boundary marking figures step by step used to depict in Fig. 5.4 and onsets of P, QRS and offsets of P, QRS and T waves are mapped on boundary values of average beat in all the average beats of 12-leads, as depicted in Fig. 5.5.

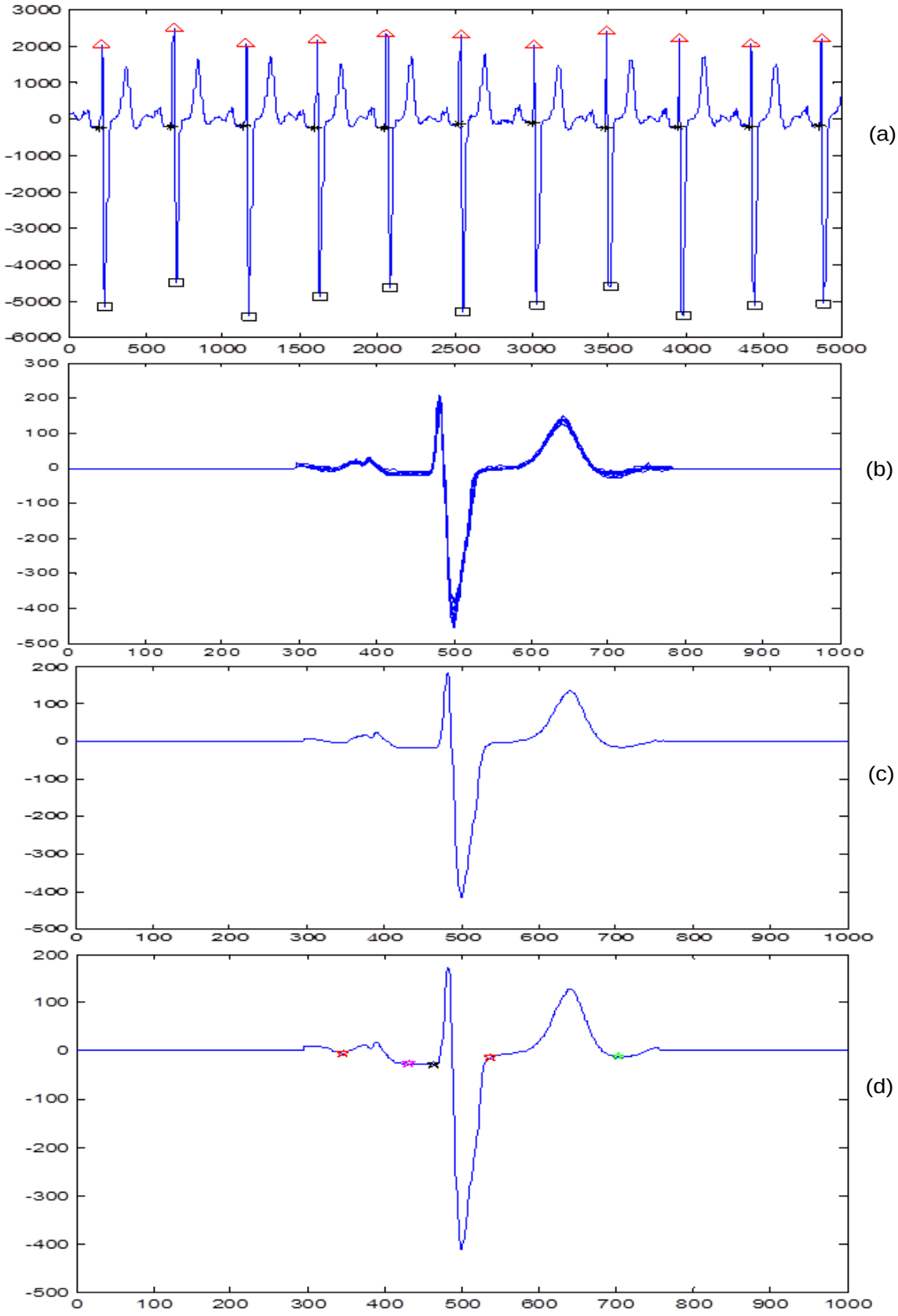

Fig. 5.4 Boundary marking step by step:(a) QRS marking of all beats of composite lead.,(b) Alignment of all beats of composite lead,(c) Average beat of composite lead, (d) Boundaries marking in the composite beat of composite lead

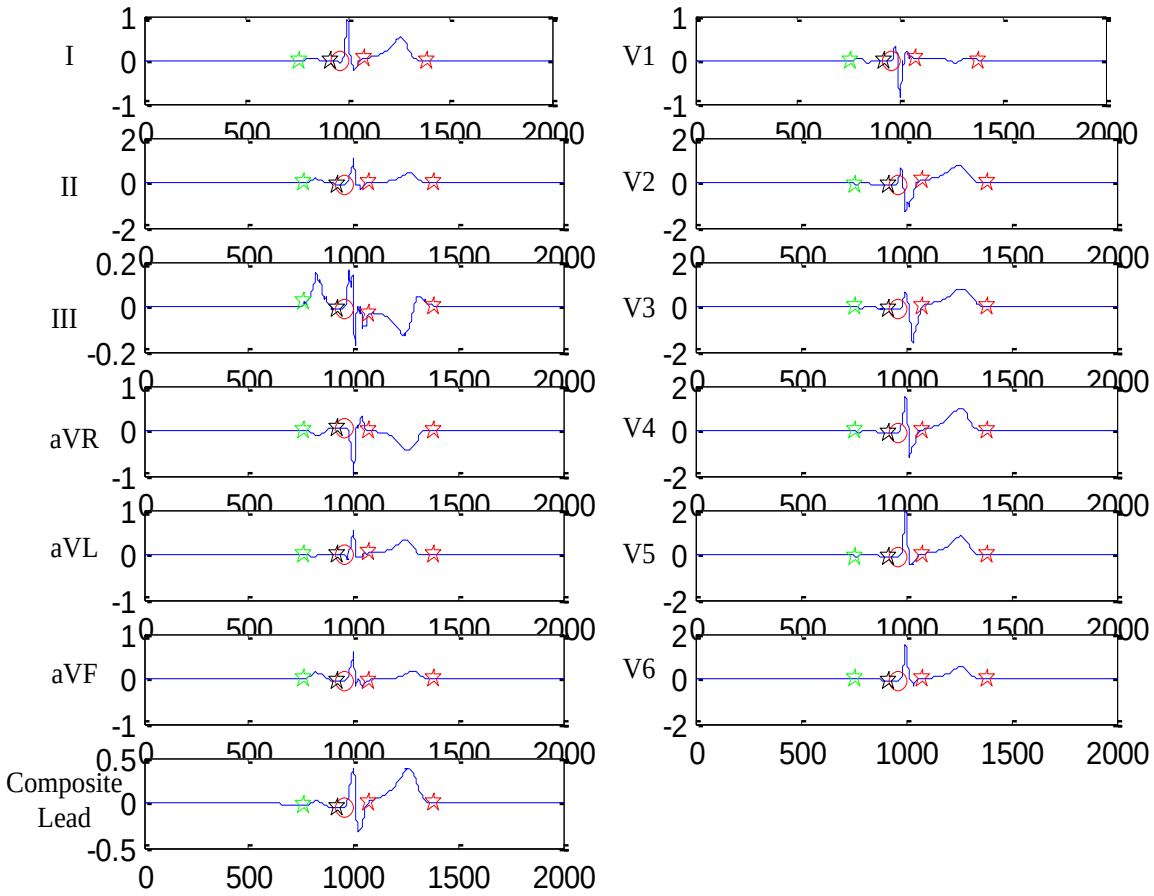

Fig. 5.5 The onsets of P, QRS and offsets of P, QRS and T wave are mapped on boundary values of average beat in all

5.3.2 Interval Calculation

After boundaries marking, four features related to wave duration and intervals are determined as depicted in Table 5.4.

Table 5.4 Interval description

S. No.	*Parameters*	Descriptions
1	*P duration*	Average duration between P_{onset} and $P_{offset,}$
2	*QRS complex duration*	Average duration between QRSonset and QRSoffset,
3	*ST-T complex interval*	The average interval between QRS_{offset} and $T_{end,}$ *and*
4	*QT interval*	The average interval between QRS_{onset} and T_{end}.

In the P duration, QRS complex duration, and ST-T complex interval of average beats of composite lead and all 12-lead ECG; determine peak to peak amplitude, area, mean, standard deviation, skewness and kurtosis of average beats ofcomposite lead and all 12-lead ECG uses MatLab functions. After determination of intervals and segments of all average beat of all 12 Lead ECG and Composite Lead. Table 5.5 depicts using formula for calculation of area, mean value, standard deviation, skewness, and kurtosis. These features are used for automated ECG classification.

Table 5.5 Calculation of area, mean value, standard deviation, skewness, and kurtosis

S. No.	*Parameters*	Descriptions
1	*Amplitude*	Peak to peak
2	*Area*	An area graph displays elements in Y as one or more curves and fills the area beneath each curve. When Y is a matrix, the curves are stacked showing the relative contribution of each row element to the total height of the curve at each x interval.
3	*Mean*	$x_{av} = \frac{1}{n}\sum_{i=1}^{n} x_i$ Where n-number of samples i-index (i=1.....n) x_i-values of points of curve
4	*Standard deviation*	Standard deviation computes the standard deviation value of the data samples between the endpoints of the selected area. The formula used to compute standard deviation is: $S = \left(\frac{1}{n}\sum_{i=1}^{n}(x_i - x_{av})^2\right)^{\frac{1}{2}}$ Where n-number of samples, i-index (i=1.....n), x_i-values of points of curve and, $x_{av} = \frac{1}{n}\sum_{i=1}^{n} x_i$
5	*Skewness*	Skewness is a statistical measure of the degree of asymmetry in a distribution (away from normal Gaussian distribution), e.g. if the distribution is weighted evenly or trends toward an edge. • A normal distribution has a skew of 0. • A distribution with a prominent left tail has a negative skew. • A distribution with a prominent right tail has a positive skew The following formula is used to extract skew: $Skew = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - x_{av})^3}{\left[\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - x_{av})^2}\right]^3}$
6	*Kurtosis*	Kurtosis indicates the degree of peakedness in a distribution, e.g. the size of the “tails” of the distribution. Distributions that have sharp peaks in their center have positive kurtosis; flatter distributions have negative kurtosis. A normal distribution has a kurtosis of 0. The following formula is used to extract kurtosis $Kurtosis = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - x_{av})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - x_{av})^2\right)^2}$

5.3.3 Conclusion

The most important aim of the automatic ECG analysis is the disease diagnosis. In general, the automatic heart disease diagnosis is being carried out by determining ECG parameters in specified limit and applying different classifier approaches. Therefore, the trustworthiness of the disease diagnosis mostly depends on accuracy of the ECG parameter estimations. As 12-Lead ECG characteristics point detection based on composite lead signal has been presented here. This proposed method was tested on standard CSE data set-3 and obtain good results. This method determines all five boundaries for each beat of composite lead signal and all 12-Leads. So each beat can be analyzed using a composite lead signal. This composite lead signal contains similar morphology of P-QRS-T with same interval and duration. The variation is only in amplitudes, hence it is more enhanced lead because it is the resultant of all 12 leads. This lead is suitable for all possible measurements and rhythm analysis. The ECG wave complexes in composite lead are noise free and enhanced in comparison to all 12 leads. The proposed composite lead method yields higher QRS detection sensitivity and positive predictivity on standard benchmark datasets which indicate its usefulness for ECG signal to mark & identify various wave components and rhythm analysis in a clinical environment in order to assist cardiologists. In this method the boundary marking is continuing in long data for each beat.

CHAPTER 6: HEART DISEASE CLASSIFICATION

In the previous chapter, wave boundaries of P-QRS-T complexes in each beat of Composite Lead has been given. Marking of ECG wave boundaries such as onsets-offset of P, QRS and end of the T wave have also been discussed.Then determine the duration and intervals of P, QRS, and T wave. On the basis of interval and duration determine other feature such as amplitude, area, mean, standard deviation, skewness and kurtosis. In this chapterthese features are used for heart disease classification with SVM and ANN classifier using different lead configuration.

6.1 Overview

In the world main causes of human death are heart disease. Heart disease cases are increasing day by day, but clinicians and cardiology expert are limited all over the world. Computer assisted medical diagnosis system can assist Clinicians or Cardiologists. The computer programs that perform diagnostic interpretation of ECG usually consist of a measurement part and classification part. In the measurement part ECG signals are analyzed and features extracted containing all necessary data for classification. On the classification part diagnostic interpretation is based on the features a classification procedure allocates the ECG to one or more diagnostic categories. The capability of a system to identify abnormalities is the detection and to characterize the detected abnormality is the classification. The detection and classification of heart diseases such as MI, CM and BB by cardiologists are based on the perspective of the human visual system. The human visual system normally faces difficulty in detection. In the present work, the ECG analysis and measurement part have been carried out through composite lead based various ECG wave components such as peak amplitude, duration, intervals and finally computation of several ECG wave parameters in composite lead and all of diagnostic significance as explained in chapter 4 and 5 of this thesis.

There are various automatic ECG analysis and interpretation programs developed by researchers in the last six decades based on heuristic [3-6, 8-11] and statistical [2, 7]. More often than not, in the heuristic approach the cardiologist provides the knowledge based decision and in the statistical approach probability density criteria. The artificial intelligence (AI) methods are more suitable for the diagnosis and classification of heart diseases. These are various methods such as Support Vector Machine, Artificial Neural Network, Fuzzy Logic methods, Hidden Markov Model, Genetic Algorithm, and Self Organizing Map.

In this work I used Support Vector Machine and Artificial Neural Network for heart disease classification. The heart disease Myocardial Infarction (MI), Cardiomyopathy (CM) and Bundle Branch Block (BBB or BB) diagnosis and classification experiment performed

based on Support Vector Machine (SVM) Classifier, and Artificial Neural Network (ANN) Classifier in this chapter.

6.2 Detection of Myocardial Infarction

The heart muscle cells require regular blood supply for keeping themselves alive and functional through two coronary arteries. If arteries or sub-branches are blocked and blood supply is interrupted, then heart suffers from ischemia and after prolonged obstruction of blood supply, heart cells die and the condition is known as myocardial infarction. The ECG testing provides information of ischemia or MI, if the patient has angina. Mostly, it is easy ways to investigate within 10 minutes, if a person has suffered from myocardial infarction taken ECGs (Electrocardiograms). Initially, if patients non diagnostic MI, serial recording performed in 15-30 minute intervals or continuous, available computerized 12-lead ECG [154]. The ECG is one of the simplest widely used noninvasive technologies for recording of electrical activity performed by heart of muscles. Fig. 6.1 depicts the Healthy Control ECG and Myocardial Infarction ECG waveform, main diagnostic wave complexes and clinical intervals measurements in of ECG signal used for manual and automatic heart diseases determination.

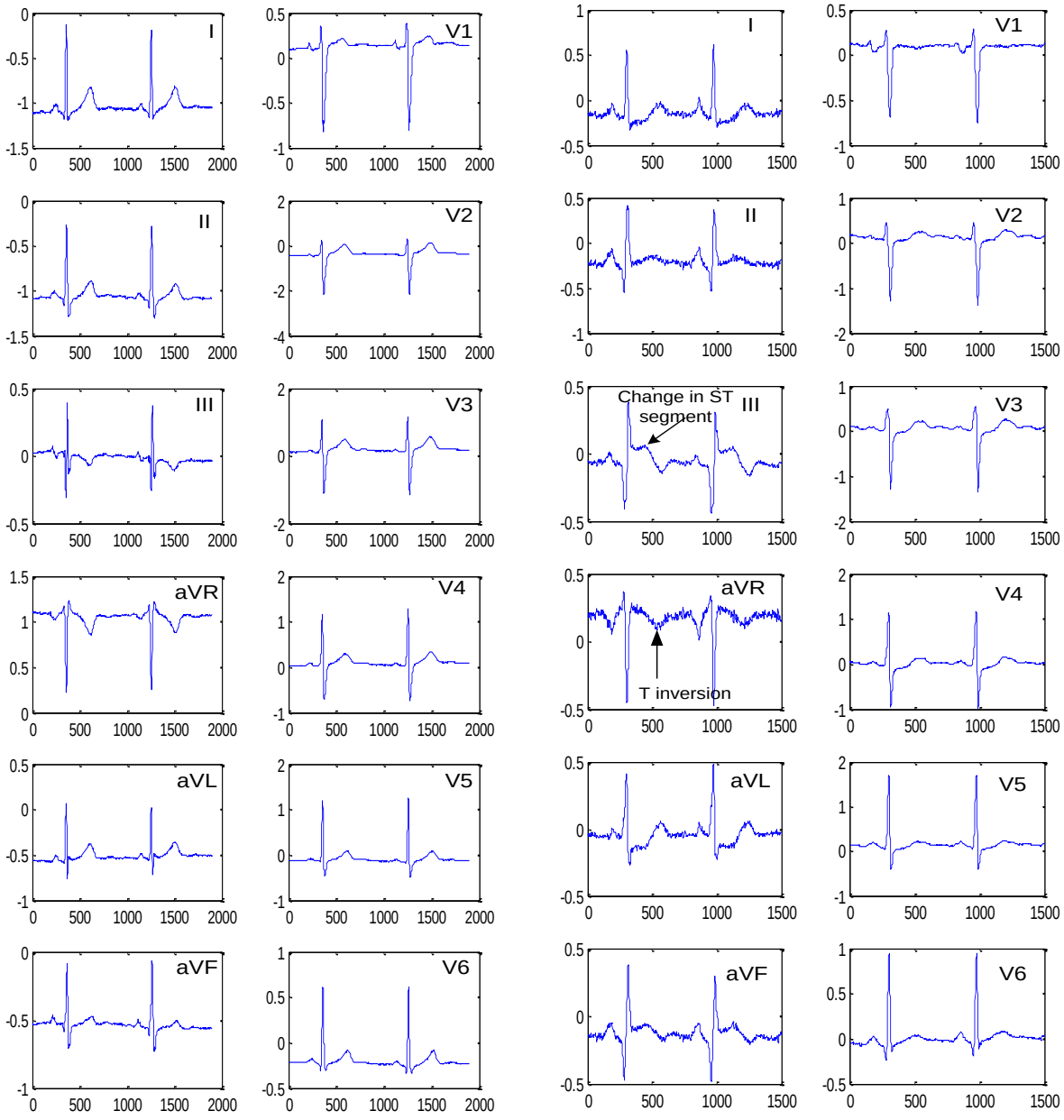

Fig. 6.1 Twelve lead ECG signals (a) Healthy Control and (b) Myocardial Infarction

Myocardial infarction is morphological disease, due to anatomical problems and produce change in the ECG waveform such as T-wave inversion, T-wave hypercute, ST elevation or depression and Q-wave variation and some studies silent Q-wave MI also associated with a significant mortality risk factor. Morphological analysis mainly based on wave shape of ECG signals. Clinician and Cardiologist easily diagnose cardiac abnormalities by visual inspection changes in ECG morphology. The morphological analysis of ECG

signals, mostly adapted for automatic classification. Computerized automatic ECG analysis represents better to visual interpretation. In order to variation in ECG MI criteria and their associations with the unrecognized myocardial infarction (UMI), ECG UMI validated by echocardiogram, magnetic resonance imaging suggested [155].

In the case of myocardial infarction change in ST segment such as elevation or depression or T wave inversion and some cases non diagnostic ECG. In many cases MI develops a change in Q wave (Q waves MI) and sometime Q wave doesn't develop (non-Q MI) [154]. In the visual analysis variety of these features observe in some particular leads whereas variations are present in all leads. In the present study we, consider all 12-lead ECG with considering diagnostic parameters such wave P wave duration QRS-complex duration, ST-T complex interval, QT interval and other parameters such as amplitude peak-peak, area, mean, standard deviation, skewness and kurtosis of QRS-complex duration and ST-T complex interval of the average beat of each 12-lead ECG. In the visual base analysis other features such as area, mean, standard deviation, skewness and kurtosis of ECG signal not compare with gold standard values. So, these parameters considered and applied ANN and SVM classifier without PCA and with PCA to classify myocardial infarction and healthy control data using Composite Lead and all lead ECG as details given in the next section.

6.2.1 Detection of Myocardial Infarction using a composite lead and all 12 Lead with SVM and ANN classifier

The Composite Lead as discussed in previous chapter 4 and 5 generated for HC and MI cases and determine features to classify HC and MI using SVM and ANN classifier. The completely developed SVM and ANN classifier system for myocardial infarction detection depicted in Fig. 6.2.

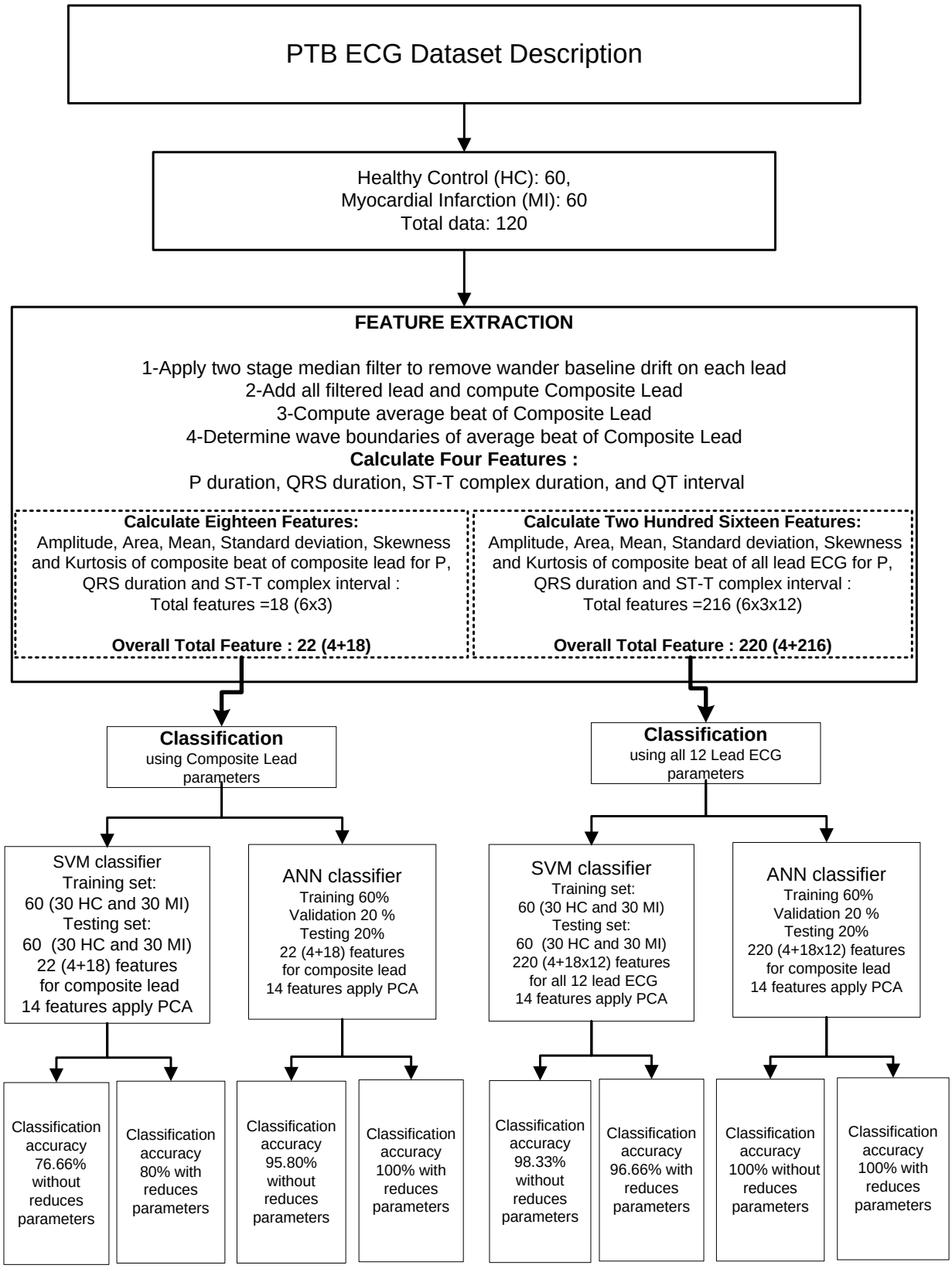

Fig. 6.2 Myocardial Infarction detection using Composite Lead and all 12 Lead ECG

6.2.1.1 Feature extraction for HC and MI data using Composite Lead

For HC and MI classification, four features carried out by calculation of intervals of P duration, QRS complex duration, ST-T complex interval, and QT interval for the average beat of Composite-Lead ECG. Eighteen features, such as amplitude peak-to-peak, area, mean, standard deviation, skewness and kurtosis of the composite beat of Composite-Lead ECG in P duration, QRS complex duration and ST-T complex interval. The total original features of Composite Lead ECGs are 22 (4+3×6).

In this study PCA is, alsoused for parameter dimensionality reduction and optimize the number of principal components (PCs) to perform HC-MI classification. Therefore, (HC & MI) reduced 14 feature obtained from 22 original feature vector. In this work 22 original and 14 reduced featurevector used to perform MI detection with SVM and ANN classifier.

6.2.1.2 Feature extraction for HC and MI data using all 12 Lead ECG

For HC and MI classification, four features carried out by calculation of intervals of P duration, QRS complex duration, ST-T complex interval, and QT interval for the average beat of all 12 Lead ECG by Composite beat of Composite Lead. Eighteen features for each lead, such as amplitude peak-to-peak, area, mean, standard deviation, skewness and kurtosis of the composite beat of all 12-lead ECG in P duration, QRS complex duration and ST-T complex interval. The total original features for a combination of all 12-lead ECG are 220 (4+3×6×12).

In this study PCA is, also used for parameter dimensionality reduction and optimize the number of principal components (PCs) to perform HC-MI classification. Therefore, (HC & MI) reduced 14 feature obtained from 220 feature vector. In this work 220 original and 14 reduced featurevector used to perform MI detection with SVM and ANN classifier.

6.2.1.3 Experimental results and discussion for MI detection performs with SVM classifier using Composite Lead 22 features

In this experiment, features extracted from the composite beat of composite lead are considered for HC-MI classification. Twenty two (4+3×6) features are used in this experiment for MI detection using binary support vector machine (SVM) classifier. In this experiment input features are normalized using min-max map scale range [-1, +1]. Here training set consists of 30 HC and 30 MI subjects and similarly another set of 30 HC and 30 MI subjects is used for testing. The execution of this experiment was depicted in Table 6.1 by selecting best regularization parameter C and the kernel parameter γ. For this experiment, the best value of C and γ was 16,684 and 0.0039 respectively, the performance class accuracy was 76.66% (58/60) and sensitivity and specificity of MI detection were 76.66% & 76%

respectively. The performance of MI detection using composite lead with original 22 features depicted in Table 6.1.

6.2.1.4 Experimental results and discussion for MI detection performs with SVM classifier using Composite Lead 14 features

To reduce the computational complexity, feature dimension reduction is significant. Thus, proposed method applies Principal Component Analysis (PCA) reduction technique. In this experiment obtained 22 parameters are reduced to 14 parameters, using these parameters MI detections achieved by SVM is: sensitivity 83.33%, specificity 76.66% and accuracy 80%. The performance of MI detection using composite lead with reduces 14 features depicted in Table 6.1.

Table 6.1 MI detection performances of 12 Lead ECG using Composite Lead feature with SVM classifier (without PCA and with PCA)

	Experiment Without PCA	Experiment With PCA
Features	22	14
Best c	16384	16384
Best γ	0.1250	9.7656e-004
Cross Validation Accuracy	100%	100%
Mean squared error (regression)	0.666667	0.666667
Squared correlation coefficient (regression)	0.935484	0.935484
Confusion Matrix (CM)	MI HC MI 23 7 HC 7 23	MI HC MI 25 5 HC 7 23
Sensitivity	76.66%	83.33%
Specificity	76.66%	76.66%
Accuracy (classification)	76.66% (46/60)	80% (48/60)

6.2.1.5 Experimental results and discussion for MI detection performs with ANN classifier using Composite Lead 22 features

In this experiment, features extracted from the composite beat of composite lead are considered for HC-MI classification. Twenty two (4+18) features are used in this experiment for MI detection. In this experiment input features are normalized using min-max map scale range [-1, +1]. Detection of myocardial infarction using extracted features of composite lead with ANN classifier, here using above 22 features and selected data 120 (60 HC & 60 MI) randomly divided into 60% training, 20% validation and 20% testing. The accuracy of the

classifier (for Testing) is 95.80%, and sensitivity and specificity of MI detection 91.70% & 100% respectively. The performance of MI detection completes depicted in Table 6.2.

6.2.1.6 Experimental results and discussion for MI detection performs with ANN classifier using Composite Lead reduced 14 features

To reduce the computational complexity, feature dimension reduction is important. Therefore, proposed method applies Principal Component Analysis (PCA) reduction technique. In this experiment obtained 22 parameters are reduced to 14 parameters, using these parameters MI detection performance (for Testing) achieved by ANN is: sensitivity 100%, specificity 100% and accuracy 100%. The performance of MI detection completes depicted in Table 6.2.

Table 6.2 MI detection performances of 12 Lead ECG using Composite Lead feature with ANN classifier (without PCA and with PCA)

Features	22	
Total data	120	
Training 60%	72	
Validation 20%	24	
Testing 20%	24	
Hidden Layer	10	
Without PCA Feature 22		
	Training CM	Test CM
Confusion Matrix (CM)	MI HC MI 34 4 HC 3 31	MI HC MI 11 1 HC 0 12
Sensitivity	89.50%	91.70%
Specificity	91.20%	100%
Accuracy (classification)	90.30% (65/72)	95.80% (23/24)
With PCA Feature 14		
	Training CM	Test CM
Confusion Matrix (CM)	MI HC MI 39 0 HC 0 33	MI HC MI 12 0 HC 0 12
Sensitivity	100%	100%
Specificity	100%	100%
Accuracy (classification)	100% (72/72)	100% (24/24)

6.2.1.7 Experimental results and discussion for MI detection performs with SVM classifier using all 12 Lead ECG 220 features

In this experiment, features extracted from the composite beat of composite lead are considered for HC-MI classification. Two hundred twenty (4+3×6×12) features are used in this experiment for MI detection using binary support vector machine (SVM) classifier. In this experiment input features are normalized using min-max map scale range [-1, +1]. Here training set consists of 30 HC and 30 MI subjects and similarly another set of 30 HC and 30 MI subjects is used for testing. The performance of this experiment was depicted in Table 6.3 by selecting best regularization parameter C and the kernel parameter γ. For this experiment, the best value of C and γ was 16684 and 9.7656e-004 respectively, the performance class accuracy was 98.33% (59/60) and sensitivity and specificity of MI detection were 96.66% & 100% respectively. MI detection performance using all 12 lead ECG original 220 features depicted in Table 6.3.

6.2.1.8 Experimental results and discussion for MI detection performs with SVM classifier using all 12 Lead ECG reduced 14 features

To reduce the computational complexity, feature dimension reduction is important. Therefore, proposed method applies Principal Component Analysis (PCA) reduction technique. In this experiment obtained 220 parameters are reduced to 14 parameters, using these parameters MI detections achieved by SVM is: sensitivity 96.66%, specificity 96.66% and accuracy 96.66%. The performance of MI detection using all 12 lead ECG with reduced 14 features depicted in Table 6.3.

Table 6.3 MI detection performances of 12 Lead ECG using all 12 Lead ECG feature with SVM classifier (without PCA and with PCA)

	Experiment Without PCA	Experiment With PCA
Features	220	14
Best c	16384	16384
Best γ	9.7656e-004	9.7656e-004
Cross Validation Accuracy	100%	100%
Mean squared error (regression)	0.666667	0.666667
Squared correlation coefficient (regression)	0.935484	0.935484
Confusion Matrix (CM)	MI HC MI 29 1 HC 0 30	MI HC MI 29 1 HC 1 29
Sensitivity	96.66%	96.66%
Specificity	100.00%	96.66%
Accuracy (classification)	98.33% (59/60)	96.66% (58/60)

6.2.1.9 Experimental results and discussion for MI detection performs with ANN classifier using all 12 Lead ECG 220 features

In this experiment, composite lead is used to detect ECG wave components and clinical wave intervals in all the 12-lead of the ECG. The clinical wave parameters such as P duration QRS duration, ST-T complex interval and QT interval globally determined average beats of all the 12 Lead ECG. Then peak to peak amplitude, area, mean, standard deviation, skewness and kurtosis for all the 12-lead ECG beats are determined for P duration, QRS duration and ST-T complex. These 220 (4+3x6×18) parameters are used for myocardial infarction detection. In this experiment input features are normalized using min-max map scale range [-1, +1]. Detection of myocardial infarction using extracted features of composite lead with ANN classifier, here using above 220 features and selected data 120 (60 HC & 60 MI) randomly divided into 60% training, 20% validation and 20% testing. The accuracy of the classifier (for Testing) is 100%, and sensitivity and specificity of MI detection 100% & 100% respectively. The performance of MI detection completes depicted in Table 6.4.

6.2.1.10 Experimental results and discussion for MI detection performs with ANN classifier using all 12 Lead ECG 14 features

To reduce the computational complexity, feature dimension reduction is important. Therefore, proposed method applies Principal Component Analysis (PCA) reduction technique. In this experiment obtained 220 parameters are reduced to 14 parameters, using these parameters MI detection performance (for Testing) achieved by ANN is: sensitivity 100%, specificity 100% and accuracy 100%. The performance of MI detection completes depicted in Table 6.4.

Table 6.4 MI detection performances of 12 Lead ECG using all 12 Lead ECG feature with ANN classifier (without PCA and with PCA)

Features	220	
Total data	120	
Training 60%	72	
Validation 20%	24	
Testing 20%	24	
Hidden Layer	10	
Without PCA Feature 220		
	Training CM	Test CM
Confusion Matrix (CM)	MI HC MI 36 0 HC 1 35	MI HC MI 15 1 HC 0 9
Sensitivity	100%	100%
Specificity	97.20%	100%
Accuracy (classification)	98.60% (71/72)	100% (24/24)
With PCA Feature 14		
	Training CM	Test CM
Confusion Matrix (CM)	MI HC MI 34 2 HC 0 36	MI HC MI 15 0 HC 0 9
Sensitivity	94.40%	100%
Specificity	100%	100%
Accuracy (classification)	97.20% (70/72)	100% (24/24)

The dimension reduction performances encourage cost reduction of the classifier. The performance of proposed simple method for MI detection is comparable and higher other researchers. The comparison of MI detection performance of the proposed method with other methods using a standard PTB diagnostic database is depicted in Table 6.5.

Table 6.5 Comparison of MI classification performance with other methods in 12-lead ECG system

S. No.	References	Classifier	Results		
			Sensitivity (%)	Specificity (%)	Accuracy (%)
1	Sharma et al [117]	SVM	93.00	99.00	96.00
2	Sun et al [118]	KNN ensemble	92. 3	88.1	NA
3	Chang et al [108]	HMM with GMM	85.71	79.82	82.50
4	Haraldsson et al [109]	Hermite with ANN	NA	NA	94.00
5	Arif et al [119]	KNN	99.97	99.9	NA
6	Reddy et al [120]	ANN	79	97	NA
7	Zheng et al [121]	SVM, Naïve	77	88.1	NA
8	Heden et al [122]	ANN	95.00	86.30	NA
9	Jayachandran et al [123]	DWT	NA	NA	96%
10	Lu et al [104]	Fuzzy logic with ANN	84.60	90.00	NA
11	Proposed method (Comp. Lead)	SVM	76.76	76.76	76.76
12	Proposed method (Comp. Lead)	SVM with PCA	83.33	76.66	80.00
13	Proposed method (Comp. Lead)	ANN	91.70	100	95.80
14	Proposed method (Comp. Lead)	ANN with PCA	100	100	100
15	Proposed method (All 12 Lead)	SVM	96.66	100	98.33
16	Proposed method (All 12 Lead)	SVM with PCA	96.96	96.96	96.96
17	Proposed method (All 12 Lead)	ANN	100	100	100
18	Proposed method (All 12 Lead)	ANN with PCA	100	100	100

6.3 Detection of Cardiomyopathy

6.3.1 Detection of Cardiomyopathy using a composite lead and all 12 Lead ECG with SVM and ANN classifier

The Composite Lead used for HC and CM cases and determines features to classify HC and CM using SVM and ANN classifier. The completely developed SVM and ANN classifier system for Cardiomyopathy detection depicted in Fig.6.3

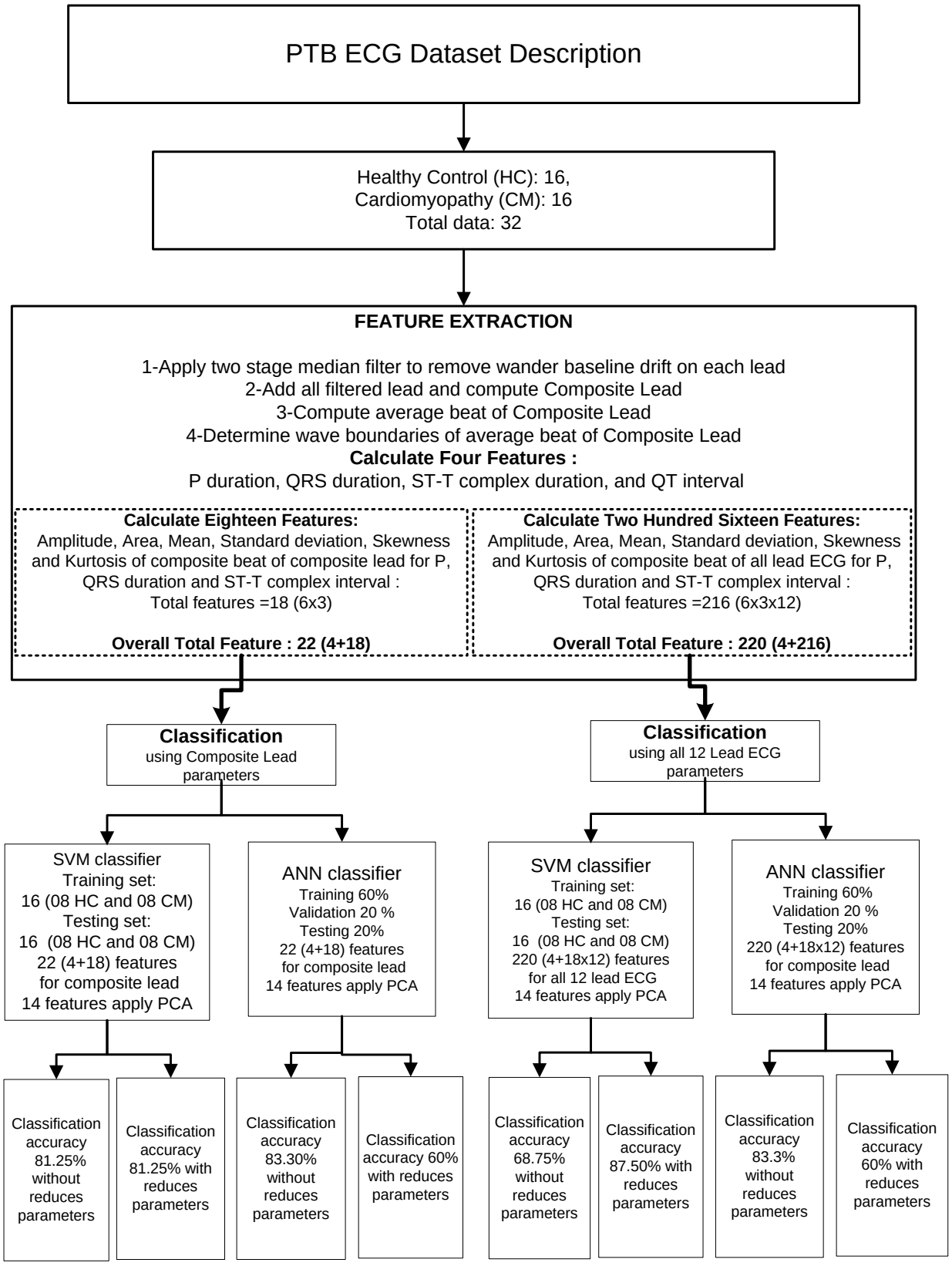

Fig. 6.3 Cardiomyopathy detection using Composite Lead and all 12 Lead ECG

6.3.1.1 Feature extraction for HC and CM for Composite Lead

For HC and CM classification, four features carried out by calculation of intervals of P duration, QRS complex duration, ST-T complex interval, and QT interval for the average beat of Composite-Lead ECG. Eighteen features, such as amplitude peak-to-peak, area, mean, standard deviation, skewness and kurtosis of the composite beat of Composite-Lead ECG in P duration, QRS complex duration and ST-T complex interval. The total features for the combination of Composite-Lead ECG are 22 (4+3×6).

Principal component analysis is a statistical method that generates a new set of variables known as principal components. In this study PCA is used for parameter dimensionality reduction and optimize the number of principal components (PCs) to perform HC-CM classification. Therefore, ECG PTB (HC &CM) dataset was calculated 22 features vector. In this work 14 PCs obtained from 22 features to perform CM detection with SVM and ANN classifier.

6.3.1.2 Feature extraction for HC and CM data using all 12 Lead ECG

For HC and CM classification, four features carried out by calculation of intervals of P duration, QRS complex duration, ST-T complex interval, and QT interval for the average beat of all 12-lead ECG by Composite beat of Composite Lead. Eighteen features for each lead, such as amplitude peak-to-peak, area, mean, standard deviation, skewness and kurtosis of the composite beat of all 12-lead ECG in P duration, QRS complex duration and ST-T complex interval. The total original features for a combination of all 12-lead ECG are 220 (4+3×6×12).

Principal component analysis is a statistical method that generates a new set of variables known as principal components. In this study PCA is used for parameter dimensionality reduction and optimize the number of principal components (PCs) to perform HC-CM classification. Therefore, ECG PTB (HC &CM) dataset was calculated 220 features vector. In this work 14 PCs obtained from 220 features to perform CM detection with SVM and ANN classifier.

6.3.1.3 Experimental results and discussion for CM detection performs with SVM classifier using Composite Lead 22 features

In this experiment, twenty two (4+3×6) features are used for CM detection with binary support vector machine (SVM) classifier. Here training set consists of 16 HC and 16CM subjects and similarly another set of 16 HC and 16 CM subjects is used for testing. The execution of this experiment was depicted in Table 6.6 by selecting best regularization parameter C and the kernel parameter γ. For this experiment, the performance classification accuracy was 81.25% and sensitivity and specificity of CM detection were 62.50% &100%

respectively. The performance of CM detection using composite lead with original 22 features depicted in Table6.6.

6.3.1.4 Experimental results and discussionfor CM detection performs with SVM classifier using Composite Lead 14 features

To reduce the computational complexity, feature dimension reduction is significant. Thus, proposed method applies Principal Component Analysis (PCA) reduction technique. In this experiment obtained 22 parameters are reduced to 14 parameters, using these parameters CM detections achieved by SVM is: sensitivity 62.50%, specificity 100% and accuracy 81.25%. The performance of CM detection using composite lead with reduces 14 features depicted in Table 6.6.

Table 6.6 CM detection performances of 12 Lead ECG using Composite Lead feature with SVM classifier (without PCA and with PCA)

	Experiment Without PCA	Experiment With PCA
Features	22	14
Best c	16384	16384
Best γ	0.0039	9.7656e-004
Cross Validation Accuracy	81.25%	100%
Mean squared error (regression)	0.1875	0.666667
Squared correlation coefficient (regression)	0.454545	0.935484
Confusion Matrix (CM)	CM HC CM 8 0 HC 3 5	CM HC CM 8 0 HC 3 5
Sensitivity	62.50%	62.50%
Specificity	100%	100%
Accuracy (classification)	81.25% (13/16)	81.25% (13/16)

6.3.1.5 Experimental results and discussion for CM detection performs with ANN classifier using Composite Lead 22 features

In this experiment, twenty two (4+18) features are used in this experiment for CM detection. Detection of myocardial infarction using extracted features of composite lead with ANN classifier, here using above 22 features and selected data 32 (16 HC &16 CM) randomly divided into 60% training, 20% validation and 20% testing. The accuracy of the

classifier is 83.30%, and sensitivity and specificity of CM detection 66.70% & 100% respectively. The performance of CM detection completes depicted in Table 6.7.

6.3.1.6 Experimental results and discussion for CM detection performs with ANN classifier using Composite Lead 14 features

To reduce the computational complexity, feature dimension reduction is important. Therefore, proposed method applies Principal Component Analysis (PCA) reduction technique. In this experiment obtained 22 parameters are reduced to 14 parameters, using these parameters CM detection performance (for Testing) achieved by ANN is: sensitivity 71.40%, specificity 33.33% and accuracy 60%. The performance of CM detection completes depicted in Table 6.7.

Table 6.7 CM detection performances of 12 Lead ECG using Composite Lead feature with ANN classifier (without PCA and with PCA)

Features	22	
Total data	32	
Training 60%	20	
Validation 20%	6	
Testing 20%	6	
Hidden Layer	10	
Without PCA Feature 22		
	Training CM	Test CM
Confusion Matrix (CM)	CM HC C M 10 0 HC 0 10	CM HC CM 2 1 HC 0 3
Sensitivity	100%	66.7%
Specificity	100%	100%
Accuracy (classification)	100% (20/20)	83.30% (5/6)
With PCA Feature 14		
	Training CM	Test CM
Confusion Matrix (CM)	CM HC CM 5 6 HC 2 3	CM HC CM 5 2 HC 2 1
Sensitivity	45.5%	71.40%
Specificity	60%	33.33%
Accuracy (classification)	50% (8/16)	60% (6/10)

6.3.1.7 Experimental results and discussion for CM detection performs with SVM classifier using all 12 Lead ECG 220 features

In this experiment, two hundred twenty two (4+3×6×12) features are used for CM detection with binary support vector machine (SVM) classifier. Here training set consists of 16 HC and 16CM subjects and similarly another set of 16 HC and 16CM subjects is used for testing. The execution of this experiment was depicted in Table 6.8 by selecting best regularization parameter C and the kernel parameter γ. For this experiment, the performance class accuracy was 68.75% and sensitivity and specificity of CM detection were 37.50% &100% respectively. The performance of CM detection using composite lead with original 220 features depicted in Table 6.8.

6.3.1.8 Experimental results and discussionfor CM detection performs with SVM classifier using all 12 Lead ECG 14 features

To reduce the computational complexity, feature dimension reduction is significant. Thus, proposed method applies Principal Component Analysis (PCA) reduction technique. In this experiment obtained 220 parameters are reduced to 14 parameters, using these parameters CM detections achieved by SVM is: sensitivity 62.50%, specificity 100% and accuracy 81.25%. The performance of CM detection using composite lead with reduces 14 features depicted in Table 6.8.

Table 6.8 CM detection performances of 12 Lead ECG using all 12 Lead ECG feature with SVM classifier (without PCA and with PCA)

	Experiment Without PCA	Experiment With PCA
Features	220	14
Best c	16384	16384
Best γ	0.0039	9.7656e-004
Cross Validation Accuracy	81.25%	100%
Mean squared error (regression)	0.1875	0.666667
Squared correlation coefficient (regression)	0.454545	0.935484
Confusion Matrix (CM)	CM HC CM 5 3 HC 0 8	CM HC CM 8 0 HC 2 6
Sensitivity	37.50%	100%
Specificity	100%	75%
Accuracy (classification)	68.75% (13/16)	87.50% (14/16)

6.3.1.9 Experimental results and discussion for CM detection performs with ANN classifier using all 12 Lead 220 features

In this experiment, two hundred twenty two (4+18×12) features are used in this experiment for CM detection. Detection of myocardial infarction using extracted features of composite lead with ANN classifier, here using above 22 features and selected data 32 (16 HC &16 CM) randomly divided into 60% training, 20% validation and 20% testing. The accuracy of the classifier (for Testing) is 83.30%, and sensitivity and specificity of CM detection 66.70% & 100% respectively. The performance of CM detection completes depicted in Table 6.9.

6.3.1.10 Experimental results and discussion for CM detection performs with ANN classifier using all 12 Lead 14 features

To reduce the computational complexity, feature dimension reduction is important. Therefore, proposed method applies Principal Component Analysis (PCA) reduction technique. In this experiment obtained 220 parameters are reduced to 14 parameters, using these parameters CM detection performance (for Testing) achieved by ANN is: sensitivity 60%, specificity 60% and accuracy 60%. The performance of CM detection completes depicted in Table 6.9.

Table 6.9 CM detection performances of 12 Lead ECG using Composite Lead feature with ANN classifier (without PCA and with PCA)

Features	22 0	
Total data	32	
Training 60%	20	
Validation 20%	6	
Testing 20%	6	
Hidden Layer	10	
Without PCA Feature 220		
	Training CM	Test CM
Confusion Matrix (CM)	CM HC C M 10 0 HC 0 10	CM HC CM 2 1 HC 0 3
Sensitivity	100%	66.7%
Specificity	100%	100%
Accuracy (classification)	100% (20/20)	83.30% (5/6)
With PCA Feature 14		
	Training CM	Test CM
Confusion Matrix (CM)	CM HC CM 6 4 HC 1 5	CM HC CM 3 2 HC 2 3
Sensitivity	60%	60%
Specificity	83.33%	60%
Accuracy (classification)	68.8% (11/16)	60% (6/10)

6.4 Detection of Bundle branch block

6.4.1 Detection of Bundle branch block using a composite lead and all 12 Lead ECG with SVM and ANN classifier

The Composite Lead used for HC and BB cases and determines features to classify HC and BB using SVM and ANN classifier. The completely developed SVM and ANN classifier system for Bundle branch block detection depicted in Fig.6.4.

6.4.1.1 Feature extraction for HC and BB for Composite Lead

For HC and CM classification, four features carried out by calculation of intervals of P duration, QRS complex duration, ST-T complex interval, and QT interval for the average beat of Composite-Lead ECG. Eighteen features, such as amplitude peak-to-peak, area, mean, standard deviation, skewness and kurtosis of the composite beat of Composite Lead ECG in

P duration, QRS complex duration and ST-T complex interval. The total features for the combination of Composite-Lead ECG are 22 (4+3×6).

Principal component analysis is a statistical method that generates a new set of variables known as principal components. In this study PCA is used for parameter dimensionality reduction and optimize the number of principal components (PCs) to perform HC-BB classification. Therefore, ECG PTB (HC &BB) dataset was calculated 22 features vector. In this work 14 PCs obtained from 22 features to perform BB detection with SVM and ANN classifier.

6.4.1.2 Feature extraction for HC and BB data using all 12 Lead ECG

For HC and CM classification, four features carried out by calculation of intervals of P duration, QRS complex duration, ST-T complex interval, and QT interval for the average beat of all 12 Lead ECG by Composite beat of Composite Lead. Eighteen features for each lead, such as amplitude peak-to-peak, area, mean, standard deviation, skewness and kurtosis of the composite beat of all 12-lead ECG in P duration, QRS complex duration and ST-T complex interval. The total original features for a combination of all 12-lead ECG are 220 (4+3×6×12).

Principal component analysis is a statistical method that generates a new set of variables known as principal components. In this study PCA is used for parameter dimensionality reduction and optimize the number of principal components (PCs) to perform HC-BB classification. Therefore, ECG PTB (HC &BB) dataset was calculated 220 features vector. In this work 14 PCs obtatine from 220 features to perform BB detection with SVM and ANN classifier

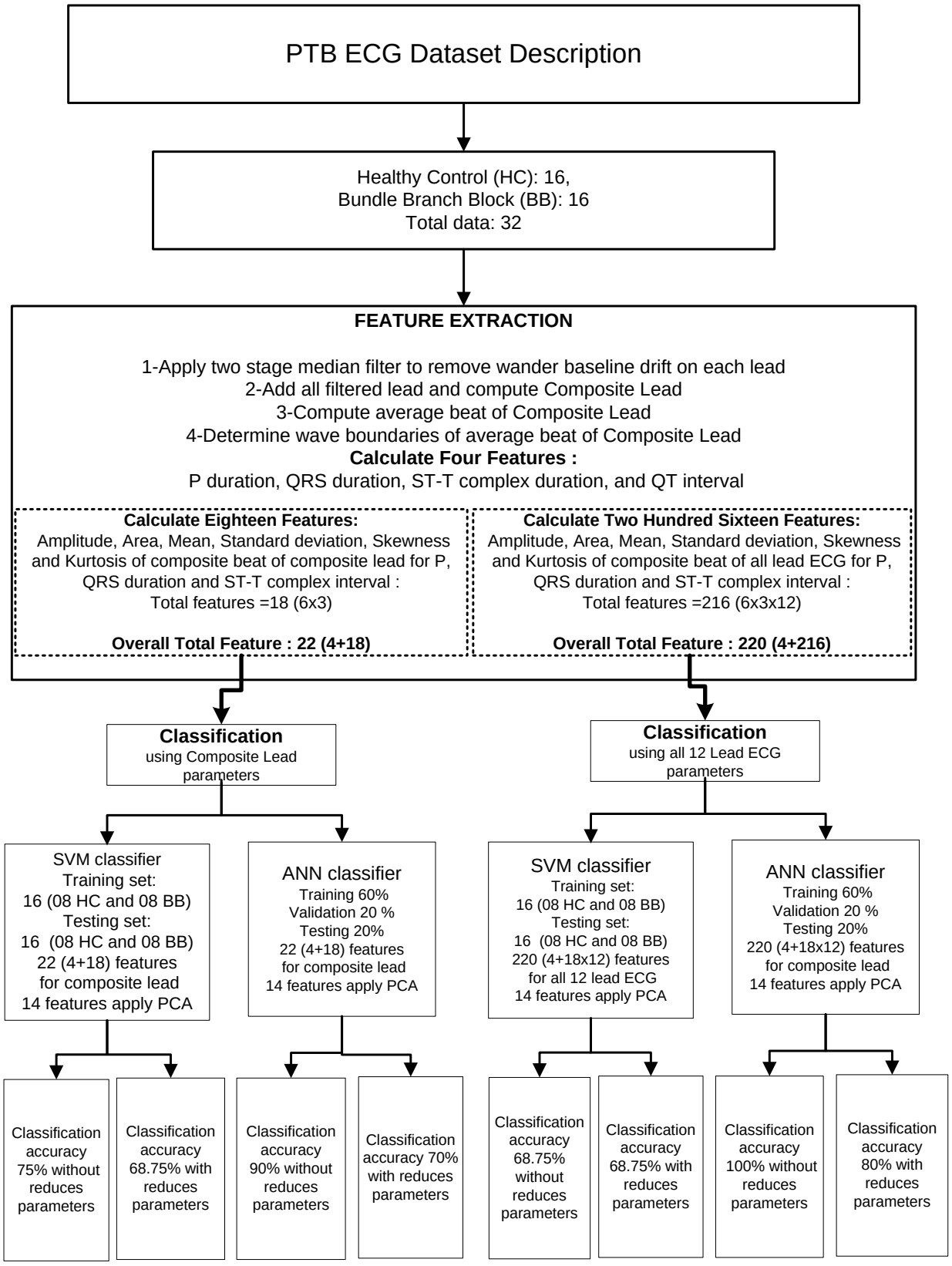

Fig. 6.4 Bundle branch blockdetection using Composite Lead and all 12 Lead ECG

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6.4.1.3 Experimental results and discussion for BB detection performs with SVM classifier using Composite Lead 22 features

In this experiment, twenty two (4+3×6) features are used for BB detection with binary support vector machine (SVM) classifier. Here training set consists of 16 HC and 16 BB subjects and similarly another set of 16 HC and 16BB subjects is used for testing. The execution of this experiment was depicted in Table 6.10 by selecting best regularization parameter C and the kernel parameter γ. For this experiment, the performance classification accuracy was 75% and sensitivity and specificity of BB detection were 50% &100% respectively. The performance of BB detection using composite lead with original 22 features depicted in Table 6.10.

6.4.1.4 Experimental results and discussion for BB detection performs with SVM classifier using Composite Lead 14 features

To reduce the computational complexity, feature dimension reduction is significant. Thus, proposed method applies Principal Component Analysis (PCA) reduction technique. In this experiment obtained 22 parameters are reduced to 14 parameters, using these parameters BB detections achieved by SVM is: sensitivity 37.50%, specificity 100% and accuracy 68.75%. The performance of BB detection using composite lead with reduces 14 features depicted in Table 6.10.

Table 6.10 BB detection performances of 12 Lead ECG using Composite Lead feature with SVM classifier (without PCA and with PCA)

	Experiment Without PCA	Experiment With PCA
Features	22	14
Best c	16384	16384
Best γ	0.0039	9.7656e-004
Cross Validation Accuracy	81.25%	100%
Mean squared error (regression)	0.1875	0.666667
Squared correlation coefficient (regression)	0.454545	0.935484
Confusion Matrix (CM)	BB HC BB 4 4 HC 0 8	BB HC BB 3 5 HC 0 8
Sensitivity	50%	37.50%
Specificity	100%	100%
Accuracy (classification)	75% (13/16)	68.75% (13/16)

6.4.1.5 Experimental results and discussion for BB detection performs with ANN classifier using Composite Lead 22 features

In this experiment, twenty two (4+18) features are used in this experiment for BB detection. Detection of myocardial infarction using extracted features of composite lead with ANN classifier, here using above 22 features and selected data 32 (16 HC &16 BB) randomly divided into 60% training, 20% validation and 20% testing. The accuracy of the classifier (for Testing) is 90%, and sensitivity and specificity of BB detection 83.30% & 100% respectively. The performance of BB detection completes depicted in Table 6.11.

6.4.1.6 Experimental results and discussion for BB detection performs with ANN classifier using Composite Lead 14 features

To reduce the computational complexity, feature dimension reduction is important. Therefore, proposed method applies Principal Component Analysis (PCA) reduction technique. In this experiment obtained 22 parameters are reduced to 14 parameters, using these parameters BB detection performance (for Testing) achieved by ANN is: sensitivity 57.20%, specificity 100% and accuracy 70%. The performance of BB detection completes depicted in Table 6.11.

Table 6.11 BB detection performances of 12 Lead ECG using Composite Lead feature with ANN classifier (without PCA and with PCA)

Features	22	
Total data	32	
Training 50%	16	
Validation 20%	6	
Testing 30%	10	
Hidden Layer	10	
Without PCA Feature 22		
	Training CM	Test CM
Confusion Matrix (CM)	BB HC BB 7 1 HC 1 7	BB HC BB 5 1 HC 0 4
Sensitivity	87.50%	83.30%
Specificity	87.50%	100%
Accuracy (classification)	87.50% (14/16)	90% (9/10)
With PCA Feature 14		
	Training CM	Test CM
Confusion Matrix (CM)	BB HC BB 7 3 HC 1 5	BB HC BB 4 3 HC 0 3
Sensitivity	70%	57.10%
Specificity	83..30%	100%
Accuracy (classification)	75% (12/16)	70% (6/10)

6.4.1.7 Experimental results and discussion for BB detection performs with SVM classifier using all 12 Lead ECG 220 features

In this experiment, two hundred twenty features are used for BB detection with binary support vector machine (SVM) classifier. Here training set consists of 16 HC and 16 BB subjects and similarly another set of 16 HC and 16 BB subjects is used for testing. The execution of this experiment was depicted in Table 6.12 by selecting best regularization parameter C and the kernel parameter γ. For this experiment, the performance classification accuracy was 68.75% and sensitivity and specificity of BB detection were 62.50% &75% respectively. The performance of BB detection using composite lead with original 220 features depicted in Table 6.12.

6.4.1.8 Experimental results and discussionfor BB detection performs with SVM classifier using all 12 Lead ECG 14 features

To reduce the computational complexity, feature dimension reduction is significant. Thus, proposed method applies PCA reduction technique. In this experiment obtained 220

parameters are reduced to 14 parameters, using these parameters BB detections achieved by SVM is: sensitivity 62.50%, specificity 75% and accuracy 68.75%. The performance of BB detection using composite lead with reduces 14 features depicted in Table 6.12.

Table 6.12 BB detection performances of 12 Lead ECG using all 12 Lead ECG feature with SVM classifier (without PCA and with PCA)

	Experiment Without PCA	Experiment With PCA
Features	220	14
Best c	16384	16384
Best γ	0.0039	9.7656e-004
Cross Validation Accuracy	81.25%	100%
Mean squared error (regression)	0.1875	0.666667
Squared correlation coefficient (regression)	0.454545	0.935484
Confusion Matrix (CM)	BB HC BB 5 3 HC 2 6	BB HC BB 5 3 HC 2 6
Sensitivity	62.50%	62.50%
Specificity	75%	75%
Accuracy (classification)	68.75% (11/16)	68.75% (11/16)

6.4.1.9 Experimental results and discussion for BB detection performs with ANN classifier using all 12 Lead 220 features

In this experiment, two hundred twenty features are used in this experiment for BB detection. Detection of bundle branch block using extracted features of composite lead with ANN classifier, here using above 220 features and selected data 32 (16 HC &16 BB) randomly divided into 60% training, 20% validation and 20% testing. The accuracy of the classifier (for Testing) is 100%, and sensitivity and specificity of BB detection 100% & 100% respectively. The performance of BB detection completes depicted in Table 6.13.

6.4.1.10 Experimental results and discussion for BB detection performs with ANN classifier using all 12 Lead 14 features

To reduce the computational complexity, feature dimension reduction is important. Therefore, proposed method applies Principal Component Analysis (PCA) reduction technique. In this experiment obtained 22 parameters are reduced to 14 parameters, using these parameters BB detection performance (for Testing) achieved by ANN is: sensitivity 80%, specificity 80% and accuracy 80%. The performance of BB detection completes depicted in Table 6.13.

Table 6.13 BB detection performances of 12 Lead ECG using Composite Lead feature with ANN classifier (without PCA and with PCA)

Features	22 0	
Total data	32	
Training 50%	16	
Validation 20%	6	
Testing 30%	10	
Hidden Layer	10	
Without PCA Feature 220		
	Training CM	Test CM
Confusion Matrix (CM)	BB HC BB 7 0 HC 0 9	BB HC BB 8 0 HC 0 2
Sensitivity	100%	100%
Specificity	100%	100%
Accuracy (classification)	100% (16/16)	100% (10/10)
With PCA Feature 14		
	Training CM	Test CM
Confusion Matrix (CM)	BB HC BB 6 2 HC 0 8	BB HC BB 4 1 HC 1 4
Sensitivity	75%	80%
Specificity	100%	80%
Accuracy (classification)	87.50% (14/16)	80% (8/10)

6.5 Design of Computer Assisted ECG Analysis and Classification (CA-ECG-AC) system for Healthy, Myocardial Infarction, Cardiomyopathy and Bundle branch block with ANN classifier

The design of CA-ECG-AC system for classification of normal, myocardial infarction, cardiomyopathy and bundle branch block heart disease was carried out with 64 twelve lead ECG from PTB database, i.e., 16 healthy control, 16 myocardial infarction, 16 cardiomypathy and,16 bundle branch block.

The proposed CA-ECG-AC system designed for Composite Lead and, 12 Lead ECG. The CA-ECG-AC system consisted of two parts: (a) feature extraction, and (b) classification. The detailed schematic diagram of classification ofnormal, myocardial infarction, cardiomyopathy and bundle branch block depicted in Fig. 6.5.

6.5.1.1 Feature extraction for HC, MI, CM, and BB using Composite Lead

For HC, MI,CM, and BB classification, four features carried out by calculation of intervals of P duration, QRS complex duration, ST-T complex interval, and QT interval for the

average beat of Composite Lead ECG. Eighteen features, such as amplitude peak-to-peak, area, mean, standard deviation, skewness and kurtosis of the composite beat of Composite Lead ECG in P duration, QRS complex duration and ST-T complex interval. The total features for the combination of Composite Lead ECG are 22 (4+3×6). In this work 22 original features to perform HC, MI, CM, and BB classification with ANN classifier.

6.5.1.2 Feature extraction for HC, MI, CM, and BB using all 12 Lead ECG

For HC, MI, CM, and BB classification, four features carried out by calculation of intervals of P duration, QRS complex duration, ST-T complex interval, and QT interval for the average beat of all 12-lead ECG by Composite beat of Composite Lead. Eighteen features for each lead, such as amplitude peak-to-peak, area, mean, standard deviation, skewness and kurtosis of the composite beat of all 12-lead ECG in P duration, QRS complex duration and ST-T complex interval. The total original features for a combination of all 12-lead ECG are 220 (4+3×6×12).In this work 220 original features to performHC, MI, CM, and BB classification with ANN classifier.

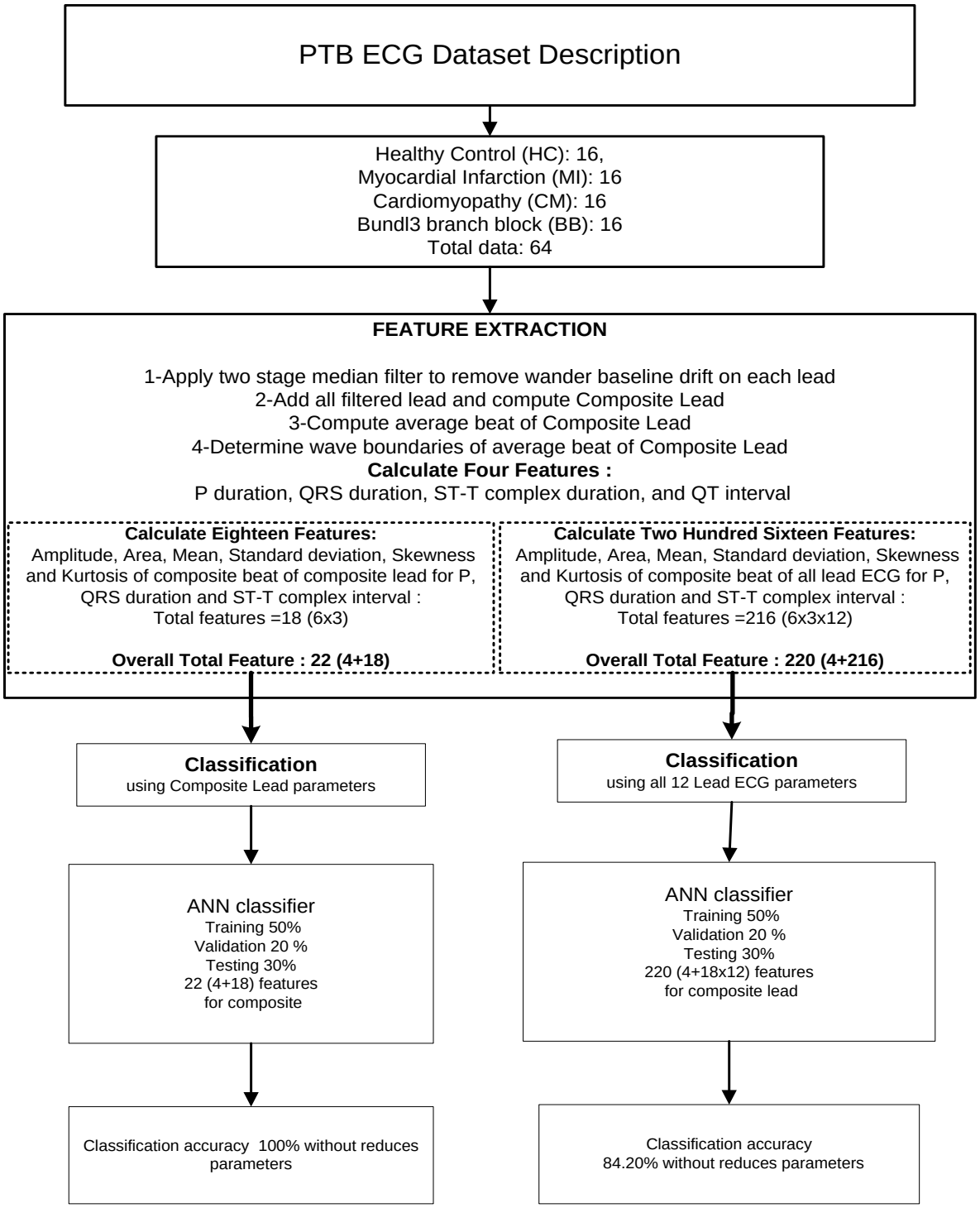

Fig. 6.5 Computer Assisted ECG Analysis and Classification (CA-ECG-AC) systemfor HC, MI, CM and BB using Composite Lead and all 12 Lead ECG

6.5.1.3 Experimental results and discussion for HC, MI, CM, and BB classification performs with ANN classifier using Composite Lead 22 features

In this experiment, features extracted from the composite beat of composite lead are considered for HC, MI, CM, and BB classification. Twenty two (4+3×6) features are used in this experiment for four class (HC, MI, CM, and BB) with ANN classifier. In this experiment input features are normalized using min-max map scale range [-1, +1]. Classification of four classes, i.e., HC, MI, CM, and BB uses extracted features of composite lead with ANN classifier, here using above 22 features and selected data 64 (16 HC, 16 MI, 16 CM & 16 BB) randomly divided into 50% training, 20% validation and 30% testing. The overall accuracy of the classifier (for Testing) is 100%. In next other time, selected data randomly devided into 40% training, 25% validation and 35% testing. The overall accuracy of the classifier (for Testing) is 100%.The performance of classifier with composite datacompletes depicted in Table 6.14 and Fig. 6.6.

Table 6.14 HC, MI, CM, and BB classification perform with ANN classifier using Composite Lead features

Composite Lead Feature 22		
Total data	64 (16 HC, 16 MI, 16 CM, 16BB)	
Training 50%	32	
Validation 20%	13	
Testing 30%	19	
Hidden Layer	10	
	Training	Testing
Sensitivity	100%	100%
Specificity	100%	100%
Accuracy (classification)	100% (16/16)	100% (10/10)

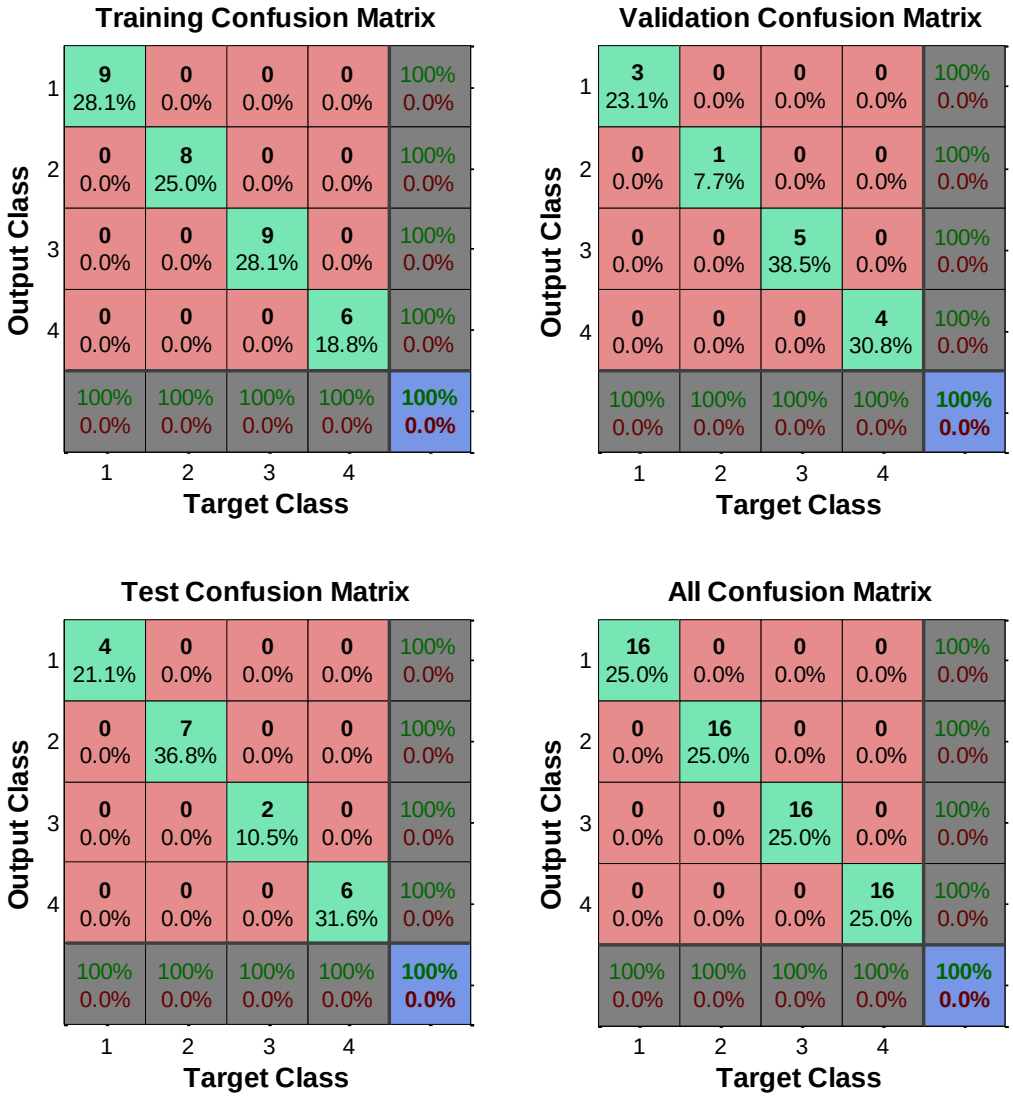

Fig. 6.6 Confusion matrix for multiclass (1-HC, 2-MI, 3-CM, and 4-BB) classification using ANN classifier with Composite Lead

6.5.1.4 Experimental results and discussion for HC, MI, CM, and BB classification performs with ANN classifier using all 12 Lead 220 features

In this experiment, features extracted from the composite beat of of all 12 lead are considered for HC, MI, CM, and BB classification. Two hundred twenty (4+3×6x12) features are used in this experiment for HC, MI, CM, and BB uses four class ANN classifier. In this experiment input features are normalized using min-max map scale range [-1, +1]. Classification of four classes, i.e., HC, MI, CM, and BB use extracted features of composite lead with ANN classifier, here using above 220 features and selected data 64 (16 HC, 16 MI, 16 CM & 16 BB) randomly divided into 50% training, 20% validation and 30% testing. The overall accuracy of the classifier (for Testing) is 84.20%. The performance of classifier with composite datacompletes depicted in Table 6.15 and Fig. 6.7.

Table 6.15 HC, MI, CM, and BB classification perform with ANN classifier using all 12 lead features

All 12 Lead Feature 220		
Total data	64 (16 HC, 16 MI, 16 CM, 16BB)	
Training 50%	32	
Validation 20%	13	
Testing 30%	19	
Hidden Layer	10	
	Training	Testing
Sensitivity	100%	100%
Specificity	100%	100%
Accuracy (classification)	100% (32/32)	84.20% (16/19)

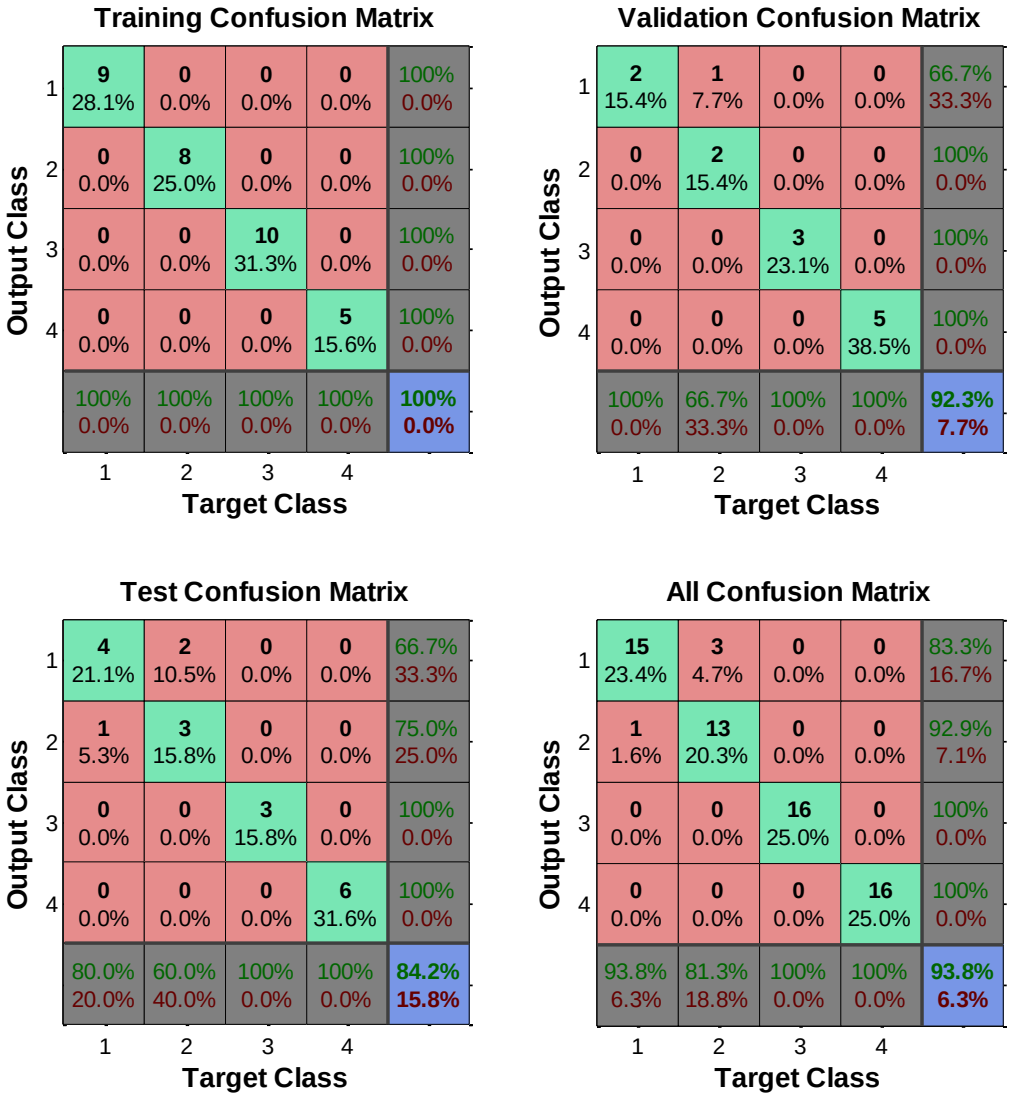

Fig. 6.7 Confusion matrix for multiclass (1-HC, 2-MI, 3-CM, and 4-BB) classification using ANN classifier with all Lead

6.6 Conclusion

In this chapter multilead ECG analysis methods as discussed in previous chapters 4 & 5 have been used for the detection of QRS complex and various ECG wave components for calculating the diagnostic features for Myocardial Infarction, Cardiomyopathy and Bundle branch block. In this workdisease diagnosis and classification were performed using different type ECG lead arrangements with SVM and ANN classifiers.

1. Detection of myocardial infarction has been performed using composite lead parameters as well as all 12 lead parameters with SVM and ANN classifiers and it is observed that ANN classifier obtained maximum accuracy in composite lead and all 12 lead systems. Also, it is observed that after reduction in dimensionality using PCA, class accuracy of 100% in both lead systems has been achieved. Thus, it can be concluded that the composite lead system performed comparable and significant MI detection.
2. Detection of cardiomyopathy has been performed using twenty two features from composite lead and 220 features from all 12 lead with SVM and ANN classifier. In this case performance of cardiomyopathy detection is higher in ANN classifier for both composite lead and all 12 lead system and it is observed that after reduction of dimensionality using PCA, performance of SVM and ANN classifiers decreased in both lead systems. Thus, it can be finally concluded that cardiomyopathy detection by the ANN classifier with a composite lead system is better than SVM.
3. Detection of bundle branch block has been performed using extracted features of composite lead and in all 12 lead systems with SVM and ANN classifiers. In this study ANN classifier performed better than SVM with all 12 lead systems.
4. The Computer Assisted ECG Analysis and Classification system designed for healthy, myocardial infarction, cardiomyopathy and bundle branch block with ANN classifier using composite lead and as well as in all 12 lead system, classification accuracy is 100% with the composite lead system and is higher than all 12 lead system.
5. Thus, it can be finally concluded that the composite lead system contributes significantly for ECG analysis and classification systems.

7.1 Conclusions

The work presented in this thesis significantly contributes to the ECG analysis and heart disease classification. This chapter summarizes the work presented in this thesis.

C*hapter 1* briefly gives the introduction of heart anatomy and heart disease significances. *Chapter 2* covers comprehensive literature review for completing research targets. Chapter 3 explains a collection of different standard ECG databases, softwares, and methodology used for performing developed algorithms in this research work.

Chapter 4 define preprocessing method for ECG signals and QRS detection for single lead and 12 Lead ECG signal. In this work, ECG signal processing and QRS detection methods for single lead were implemented on all standard databases such as CSE, MIT/BIH arrhythmia, ESC ST-T, QT database, and MIT/BIH Noise Stress database. For single lead QRS detection was applied on 380 cases and overall QRS detection performance are: Sensitivity 99.52% and positive predictivity 99.69%. The methods developed for multilead QRS detection were applied on the CSE ECG database, St. Petersburg Institute of Cardiological Technics 12-lead Arrhythmia Database, PTB database. The performance of the algorithm is evaluated against CSE (Common Standards for Quantitative Electrocardiography) multilead measurement database and St. Petersburg Institute of Cardiological Technic's 12-lead Arrhythmia Database. The detection sensitivity (Se) and positive predictivity (+P) of CSE multilead measurement data set-3 original & artificial, and data set-4 original & artificial are Se 99.87% & +P 100%, Se 100% & +P 100%, Se 99.49% & +P 99.80%, and Se 100% & +P 100% respectively. The QRS detection performance of the proposed method is depicted for PTB Database as 58 false positives and 2 false negatives, resulting in QRS detection sensitivity (Se%) and positive predictivity (+P) as 99.90% and 100% respectively, for all 12 leads and the composite lead.The QRS detection performance on a Holter recording 12-Lead data using the St. Petersburg Institute of Cardiological Technics 12-lead Arrhythmia Database (30 minute data) determined the sensitivity and positive predictivity as 95.13% and 99.92% respectively. The overall performance of the proposed method, using different standard multilead databases, such as CSE, PTB and St. Petersburg multilead Arrhythmia with different cases and total 2,55,925 beat analysis is average sensitivity of 99.24% and positive predictivity of 99.90%.

In *chapter 5* the boundary marking using composite lead in CSE measurement data set-3 for P_{onset}, P_{offset}, QRS_{onset}, QRS_{offset} and T_{end} estimates are within limits as recommended by the CSE working party. The boundary marking measurements were compared with referee results and twenty CSE programs. The results of the proposed method for boundary marking are comparable and within CSE recommendations. For P_{onset} and P_{offset} analysis, mean differences are calculated and mean error is determined as -4.28 and 1.4 with the

standard deviation values equal to 4.42 and 6.02 respectively. Similarly, for QRS_{onset}, QRS_{offset}, and T_{end} mean error values are 0.12, -0.76 & -1.92 and standard deviation values being 2.5, 4.30 and 11.39 respectively. All measurements are in samples.

In *chapter 6*, the above methods have been used for the detection of QRS complex and various ECG wave components for calculating the diagnostic features for Myocardial Infarction, Cardiomyopathy and Bundle branch block. Heredisease diagnosis and classification were performed using different ECG lead arrangements with SVM and ANN classifiers. Detection of myocardial infarction has been performed using composite lead parameters, all 12 lead parameters with SVM and ANN classifiers and it is observed that ANN classifier obtained maximum accuracy in composite lead and in all 12 lead systems. Also, it is observed that after reduction in dimensionality using PCA class accuracy obtained is 100% in both the lead systems. Thus, it can be concluded that the composite lead system performed comparable and significant MI detection. Detection of cardiomyopathy has been performed using twenty two features from composite lead and 220 features from all 12 lead system with SVM and ANN classifier. In this case performance of cardiomyopathy detection is higher in ANN classifier for both composite lead and all 12 lead system and it is observed that after reduction in dimensionality using PCA performance of SVM and ANN classifiers decreased in both the lead systems. Thus, it can be finally concluded that cardiomyopathy detection with ANN classifier with a composite lead system better than SVM. Detection of bundle branch block has been performed using extracted features of composite lead and all 12 lead systems with SVM and ANN classifiers. In this study ANN classifier performed better than SVM with all 12 lead systems. The Computer Assisted ECG Analysis and Classification system designed for healthy, myocardial infarction, cardiomyopathy and bundle branch block with ANN classifier using composite lead and all 12 lead featureshas obtained class accuracy 100% with the composite lead system. Thus, it can be finally concluded that the composite lead system contributes significantly for ECG analysis and classification systems.

7.2 Scope for future work

1. In this study, the time domain features are used for normal, myocardial infarction, cardiomypathy and bundle branch block classification using composite lead and all 12 lead ECG. Features can be extracted from domain transform and can be used for disease classification.
2. Patient history with morphological features can be added for better classification of heart diseases.
3. Approach presented here can be extended for classification of more cardiac abnormalities that is arrhythmias, ischemia, etc.

PUBLICATIONS FROM THE WORK

Journals

[1] A. K. Dohare, V. Kumar, R. Kumar **"**An Efficient New Method for the Detection of QRS Complex in Electrocardiogram**"**, Computers & Electrical Engineering, Vol. 40, No. 4 pp 1717–1730, 2014. [Elsevier Journal, Impact Factor: 0.97, SCI]

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[3] A. K. Dohare, V. Kumar, R. Kumar, "Detection of Myocardial Infarction in 12 lead ECG using Support Vector Machine" submitted in Applied Soft Computing Journal [under review].

[4] A. K. Dohare, V. Kumar, R. Kumar "12-Lead ECG Analysis and classification Based on Composite lead Signal Using ANN",submitted in Biomedical Signal Processing & Control [under review].

International conferences

[1] A. K. Dohare, V. Kumar, R, Kumar "A New Efficient Method for QRS Detection in 12_Lead Electrocardiogram" In Proceeding of 2nd International Conference on Biomedical Engineering and Assistive Technologies (BEATS 2012), National Institute of Technology, Jalandhar, India, 6-7 December 2012.

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