ELECTROCARDIOGRAM SIGNAL PROCESSING

AND

CLASSIFICATION

A Dissertation Submitted in Partial Fulfillment of the Requirement for the Award of the Degree of

MASTER OF ENGINEERING

IN

ELECTRONICS AND COMMUNICATION ENGINEERING

Submitted By

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JUNE, 2017

DECLARATION

I, **Amandeep Kaur** hereby declare that the work presented in this thesis entitled "**Electrocardiogram Signal Processing and Classification**" in partial fulfillment of the requirement for the award of degree of Master of Engineering submitted at Electronics and Communication Engineering Department, Thapar University, Patiala is an authentic record of work carried out under supervision of **Dr. Sanjay Kumar** (Associate Professor, ECED, Thapar University, Patiala). The matter presented in this has not been submitted either in part or full to any other university or institute for the award of any other degree.

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It is certified that the above statement made by the candidate is correct to the best of my knowledge and belief.

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ACKNOWLEDGEMENT

I would like to express my sincere gratitude to my research advisor Dr. Sanjay Kumar for his support and guidance during my course work. I have been inspired by his meticulousness, his attention to detail and his energetic application to any problem. I value his concern and support at all times, good and bad. He has always emphasis on self-motivation during rough or bad periods and appreciated in good days. The words are not enough to thank him.

I am also thankful to Thapar University for the facilities and healthy environment for study. I also express my sincere thanks to my Head of the Department, Dr. Alpana Aggarwal for providing me adequate environment in carrying the work.

A big thanks to my friend Ishan Chawla for his support in accomplishment of my course work. He always taught me the patience and never to give up attitude in the research work. I would like to thank Manisha Singla for helping me wherever I required.

I would like to thanks my parents for raising me, believing in me, allowing me to do things in my way and to agree with me even if they don't want. The presence of my brother and sisters is always supporting and loving in every aspect of my life.

I would also like to acknowledge the Department of Science and Technology (DST) for making me the part of the research project sanctioned by Science and Engineering Research Board (SERB) and providing all the required support.

Finally, I would like to extend my gratitude to all those persons who directly or indirectly helped me in the process and contributed towards this work.

Above all I thank the Almighty God who is being with me and showers his blessings and his grace towards me in all walks of my life.

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ABSTRACT

The purpose of the reported work is to provide unified introduction to the principles and applications of wavelet transform (WT) in the biomedical ECG signal. WT has proven to be powerful tool for analysis of non-stationary (time-varying) signals by providing simultaneous time-frequency resolution.

As it is evident from literature that fourier transform (FT) does not reflect evolution over time of the spectrum and thus it contains no local information. WT has overcomes the drawbacks of FT by representing signals (time-dependent signals) in the phase-space (time-frequency plane), with local time-frequency resolution. Thus, WT provides an excellent time-resolution of high-frequency components and a frequency (scale) resolution of low-frequency components.

There exists various wavelet based techniques such as continuous wavelet transform (CWT), discrete wavelet transform (DWT), wavelet packet analysis (WPA) as well as Mallet filtering scheme and algorithm for the DWT based calculations.

In the proposed work, DWT have been thoroughly studied and applied for the analysis of biomedical ECG signal. The raw ECG data is obtained from MIT-BIH database that contains both normal as well as abnormal subjects. The filtering operation is performed on raw data for removal of noise present in the obtained ECG. Further, various artifacts are removed by denoising procedure which utilized WT techniques. Thus an appropriate mother wavelet and efficient thresholding techniques and methods will be required to obtain clean ECG free from all noises and commotions.

After denoising, feature extraction is done so as to transform existing features into a lower dimensional space. The various features like P-QRS-T wave peaks, QRS, PR, RR intervals and ST segment are extracted from ECG signal.

Finally, classification of ECG is performed using support vector machines (SVM), adaptive boosting (AdaBoost), random forest, neural network (NN) and decision tree. The performance matrix of classification such as accuracy, positive predicitivity and sensitivity are obtained.

TABLE OF CONTENTS

List of Tables

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 GENERAL

AN ELECTROCARDIOGRAM (ECG) is the prominent and principal tool used for diagnosis and prognosis analysis of the heart diseases by cardiologists. It is a record of the electrical commotion caused by depolarization and repolarization of the atria and ventricles of the heart muscles. ECG signals have a wide array of applications in biomedical field in determining the functioning of the heart. Thus it is the golden standard for the cardiac diseases.

Recently biomedical signal processing is the most heated topic among researchers. Their focus is to improve the data analysis of automatic systems. The values obtained during the ECG recording form the basis whether the signal is normal or abnormal. As the observation of these values is inexplicit, existence of automatic detection system is necessitated. ECG signal being non-stationary makes clinical observation a tedious job. Moreover, it is difficult to rely upon visual analysis of ECG signals. Thus, there is a need for computer based techniques for ECG analysis.

Electrocardiography is an essential device to estimate information about normal or abnormal action of heart. As nowadays heart diseases are a common reason of death for people in most of the developed countries. As per the WHO report in 2007 the overall death was 251.7 due to heart diseases per 100,000 population [1]. The death rates vary for gender and races. This highly increase in deaths due to heart problems in modern era is due to obesity, diabetes, smoking and sedentary lifestyles.

ECG signal is a periodic signal that reflects the electrical activity of the heart. It consists of repeatedly heart beats. A lot of information on normal and pathological physiology of the heart is acquired from ECG signal. Each beat contains many waves and interweaves. The length and appearance will indicate different heart diseases. The time and amplitude axis are indicated by seconds and millivolts respectively.

ECG beat generated in body and propagation of its waves in the body is shown in Fig.1.1. P-wave, Q-wave, R-wave and S wave are different wave components in the beat. P-wave shows activation (depolarization) of atria as blood moves form atria to ventricles as clearly depicted in Fig. 1.1. P-Q interval indicates that a wave is generated from atria to ventricles. QRS complex shows the depolarization of ventricles. T-wave indicates recovery wave of ventricles (repolarization of ventricles).

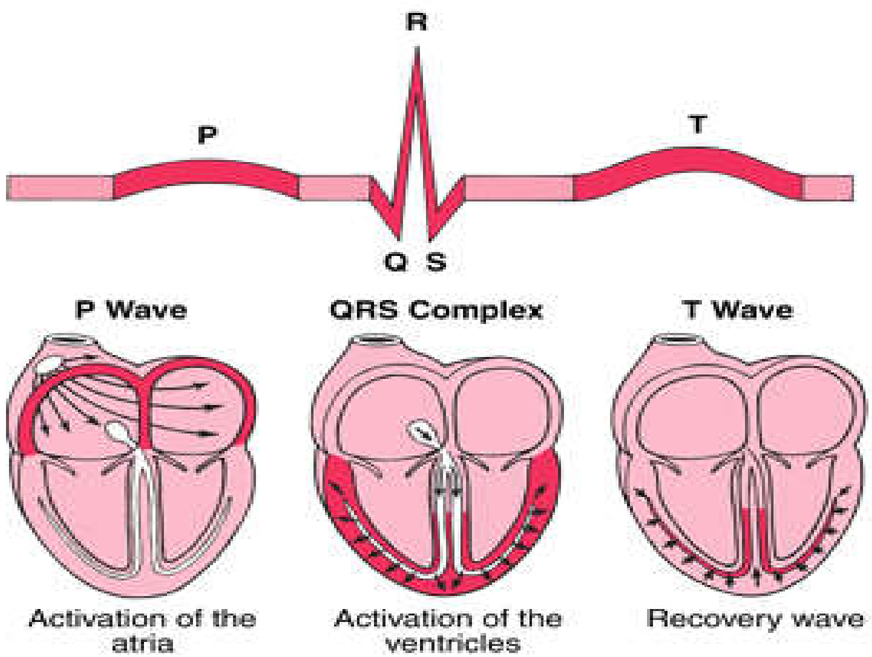


Fig. 1.1 Propagation of ECG wave [2]

The muscles of heart can prove to be a reason for rhythm disorder. It is an obstacle for pumping of blood, thus increasing the risk of death. Since it is critical to monitor the situation of patient heart, various methods for automatic detection are there, but most of them have high computational complexity to extract features and they can classify a limited disease types.

1.2 VARIOUS METHODS AND TRANSFORMS IN ECG ANALYSIS

Since ECG is a non stationary signal, **Fourier Transform** (FT) and **Short Time Fourier Transform** (STFT) have failed in analyzing it. FT provides information whether particular frequency components are present or not independent of where in time these components occur or appear. STFT provides simultaneous time and frequency resolution. But it has its own shortcomings as it has fixed window size, due to which it has fixed resolution. This limitation roots go back to Heisenberg Principle. In Fig 1.2 and Fig. 1.3 shows the time and spectral resolution of STFT.

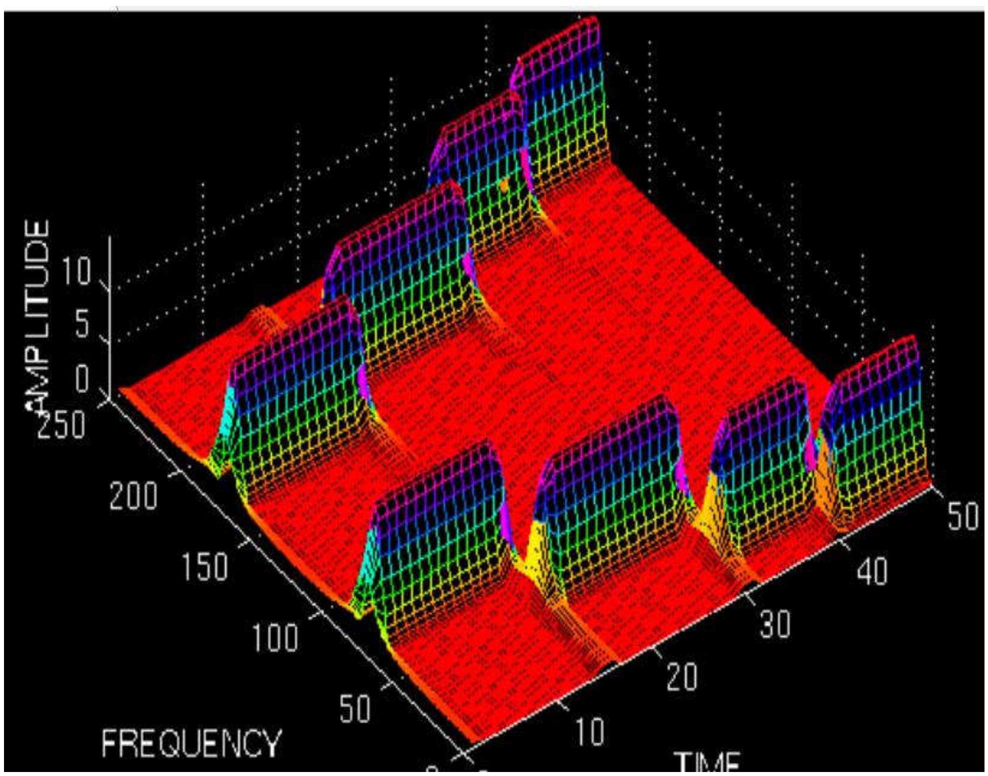


Fig 1.2 Good resolution of STFT in time [2]

If the window in STFT is narrow, the time resolution is better and frequency resolution is poor as shown in Fig. 1.2. If window is wide, better is frequency resolution as shown in Fig. 1.3 and poorer time resolution. Thus it is difficult to decipher the hidden details in ECG signal. Therefore a tool or technique is required which will prove very helpful to the physicians in the diagnosis and interpretation of cardiovascular diseases.

In past decades, extensive research has been done to develop a tool, algorithms or methods based on microprocessor or minicomputers to allow cardiologists to derive hidden information for diagnosis purposes. This work generally consists of involving automatic rhythm analysis, classification and diagnosis with different accuracy and sensitivity.

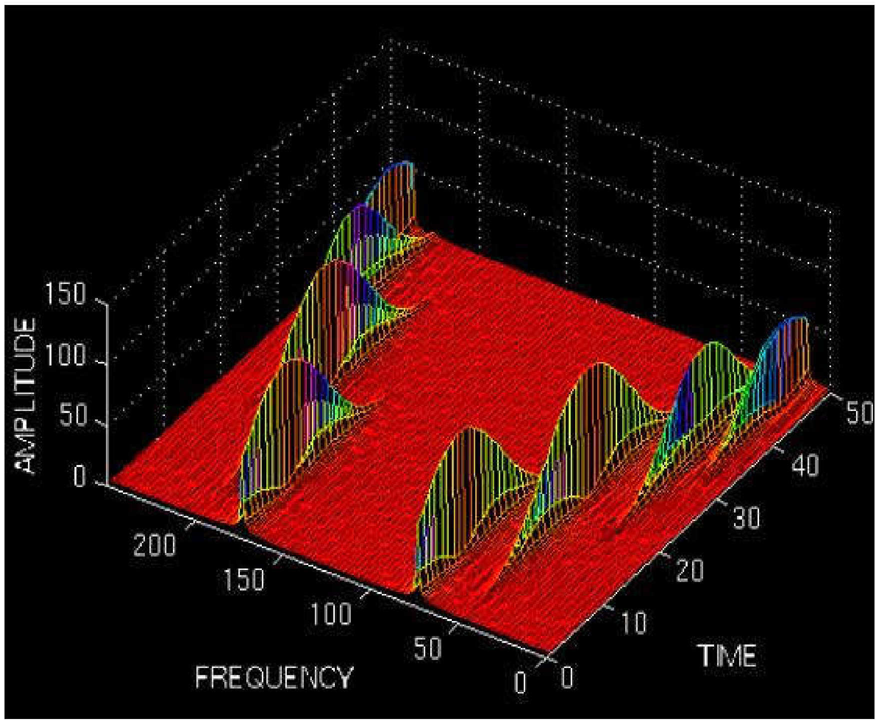


Fig 1.3 Good resolution STFT of in frequency [2]

Ventricular Premature Contraction (VPC) beat in ECG was detected with a sensitivity of 92% using linear prediction method [3]. Using Hidden Markov Model (HMM), various ECG segments were examined and eventually classified ECG beats into normal, supra-ventricular ectopic beats and ventricular ectopic beats using time domain features [4]. The morphology and RR interval features of ECG data were used as the basis for the classification into different beats using particular swarm optimization and reported accuracy of 93.27% was obtained [5]. The ECG beats were classified with 96% accuracy using Hermite coefficients and neuro-fuzzy [6].

Wavelet transform and principal component analysis (PCA) were used to categorize ECG beats into normal and abnormal by employing various classifiers and an accuracy of 95.6 was estimated using SVM classifier [7]. However all these methods were not fully efficient.

Following this interpretation, Wavelet Transform (WT) and Discrete Wavelet Transform (DWT) was developed for examining non stationary signals like ECG. It was introduced way back in 1982s, to analyze seismic signals but now it is used in all modern applications such as signal processing, image processing, pattern recognition and other medical and biomedical signal and image technology. Wavelet also enables composite information such as music, speech, images and patterns to break up into basic forms by varying positions and scales and eventually reconstructed with high precision.

1.3 CLASSIFICATION IN ECG

Classification is the process of discovering new data into predefined classes on the basis of training set of data containing observation. Classification is executed by classifier which is an algorithm or sometimes refers to a mathematical function that maps input data into different groups or classes. In ECG signal processing, classifiers classify ECG beats into various types, but here only normal and abnormal type of classes are used. They perform classification using some prior information about ECG statistical knowledge embedded in the data or some sets of features extracted from the temporal and morphology of signal.

First, data acquisition is the most important section in which raw ECG data are obtained which is intended for further classification. Second, feature extraction part is responsible to extract unique information from the raw data. Third, is the feature selection section in which optimal features are selected from the feature extracted. Fourth and the final classification section classify the input raw data into predefined classes by using extracted features.

Various classifiers such as K-nearest neighbor, Support Vector Machine (SVM), Neural Network (NN), Random Forest, Decision Tree, Adaptive Boosting (AdaBoost) and so on. Implementation of these methods requires statistical, temporal and morphology details of the signal. Thus, it needed a procedure for selecting features which are really necessary and adjusting the model parameters.

Selecting the appropriate classifier is problem or situation dependent as there is no such single classifier that works best on all given datasets or problems as explained by *no free lunch theorem* [8]. Classifiers performance is highly dependent on the properties of the data to be classified. A lot of different tests have been conducted to estimate the classifier performance and to obtain the attributes of the data that control classifier performance. Finding the apt classifier for a dataset is still an art more than science.

1.4 OUTLINE OF THE THESIS

The entire thesis is organized into six chapters. The chapter wise summarization is given below:

Chapter 2: Literature Review

This chapter presents the rigorous literature review for the research work. It presents the evolution of wavelet transform from fourier transform. It also contains FIR filtering, wavelet in ECG and its classification.

Chapter 3: ECG signal denoising using wavelet transform

Following the literature review in Chapter 2, wavelet transform is employed in ECG for removing various artifacts superimposed in ECG. A brief review of wavelet and wavelet transform is provided. The selection of optimal wavelet function, thresholding function and Donoho value for denoising is presented. Finally, the denoised ECG is demonstrated in the simulation results.

Chapter 4: Feature Extraction

This chapter focuses on pre-processing and feature extraction in ECG. The algorithm is proposed for the feature extraction in ECG, covering all the important characteristics of ECG and making a feature vector from them.

Chapter 5: Classification

Classification of ECG beat is discussed in this chapter. The various classifiers and their working are briefly explored. Then, the performance evaluation of all the mentioned classifiers is clearly stated in the chapter.

Chapter 6: Conclusions and Future scope of the work

Finally, the conclusions of the proposed work along with the future scope is presented and discussed in this chapter.

CHAPTER 2

LITERATURE REVIEW

A THOROUGH ANALYSIS of literature review is essential for the productive and good research work. Literature review is acquiring an author's phenomena, methodology and history. It helps to understand the evolution of technology.

2.1 FROM FOURIER TO WAVELET TRANSFORM

In 19th century, the French mathematicians J. Fourier showed that any periodic signals can be expressed as an infinite sum of periodic complex exponential functions. Many years later his idea was extended to non periodic, periodic and non periodic discrete signals or functions. Fourier Transform (FT) is defined by following formula:

$$F(\omega) = \int_{-\infty}^{\infty} f(t)e^{-j\omega t}\,\mathrm{dt} \tag{2.1}$$

$$f(t) = \int_{-\infty}^{\infty} F(\omega)e^{j\omega t}d\omega \tag{2.2}$$

Thus the integral in (2.2) over time that goes from minus infinity to infinity provides information about the frequency contents of signals which are present or not. It does not provide any information about frequency content of signal. Thus it is unsuitable for non stationary signals.

Thus to overcome the drawbacks of FT, **Short Time Fourier Transform (STFT)** was introduced. In STFT, the signal is segmented into small portions and these portions are assumed to be stationary. Thus the window function is chosen and width of the window is made equal to the portions of the signals where its stationarity is valid. The definition of STFT is given as:

$$STFT(l,\omega) = \int_{-\infty}^{\infty} f(t)\omega'(t-l)e^{-j\omega t}dt \tag{2.3}$$

In (2.3) $f(t)$ is the non stationary signal, $\omega'(t)$ is the window function and l is the amount of shifting in time domain. The width of window is the most important factor in STFT. The drawback of STFT goes back to Heisenberg's uncertainty principle (discussed in chapter 3) which states that exact time-frequency representation of the signal can't be known i.e. it is complicated to know exact spectral components at the particular period of time [10]. Thus band of frequencies present is known at a particular time interval. As STFT has fixed window resolution as shown in Fig.2.1, therefore it is not suitable for non-stationary signals. In Fig. 2.1 shows the resolution of STFT.

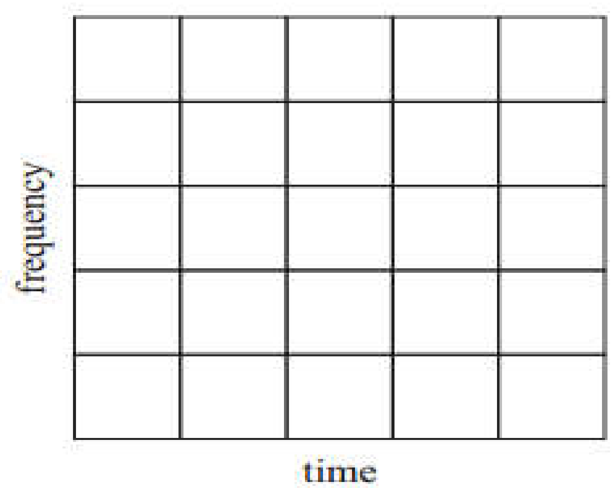


Fig. 2.1 Resolution of STFT [3]

The narrow is the window, better is the time resolution but poor is the frequency resolution and better is stationarity assumption and vice versa.

Wavelet Transform (WT) is designed to give good time resolution and poor frequency resolution at the high frequencies and good frequency resolution and poor time frequency resolution at the low frequencies. Since WT has varying time-frequency resolution, so this approach is very beneficial when the signals have high frequency for short duration and low frequency for long duration which is mainly in biological signals like ECG, EEG, etc.

Cohen *et al.* [10] explained the concept of the joint time-frequency analysis. It is divided into two categories: linear and quadratic. All the methods introduced in this section are those signals whose frequencies do not change over time rapidly.

Qian *et al.* [11] presented that the frequency representation can't alone study or analysis dynamic aspects of structures are not easily studied with frequency representation alone. Thus the coupling between modes, identification frequency shifting and temporal location of modal response is included.

Baseline drift in ECG waveform affect the visual scrutiny of the ECG. **Pandit** [12] investigated the usefulness of STFT in estimating the presence of baseline wander which is a low frequency component is removed by implementing the time varying digital filters. Thus time-frequency analysis like STFT to remove baseline wander was discussed. If baseline drift varies with time, limitation of STFT approach to baseline drift elimination in the waveform.

Aquil *et al.* [13] evaluated the performance of Continuous Wavelet Transform (CWT), STFT, Wigner Ville transform, Choi Williams transform and an algorithm based on CWT coefficients for R-peak detection. The study proved that CWT locates R-peak with a comparatively less processing time. R-wave has higher energy as contrast to other waves in ECG waveform. To hasten the detection of R-peaks an algorithm was suggested where scale is selected for which the signal energy is higher. Once the scale is fixed an average of coefficients of CWT is calculated for the chosen scale. This perspective can be extended to find other peaks of ECG waveform.

2.2 FIR FILTERING

Digital filters are backbone of signal processing. With the advancement of technology, application of digital filters is extended to various fields such as communication, voice and image processing and so on. Based upon time domain behavioral response characteristic digital filters are categorized into two types: Finite Impulse Response (FIR) and Infinite Impulse Response (IIR).

Li *et al.* [14] designed and simulated FIR band pass filter using window function method in MATLAB. It is clearly stated that besides designing the filters by computer aided software due to development in technology and large scale integration, it also helps to attain optimization in filtering. Designing filters in MATLAB saves programming time, thus enhancing efficiency of programmer and programming. It also provides a convenient way to parameter changes.

Eleti *et al.* [15] reported that FIR filters are used for filtering with the purpose to improve the frequency characteristics of the filter at a particular time. This is used in many applications like data compression, biomedical signal processing and so on. The window method is easy to understand. The main drawback is inability to specify the pass band and stop band frequencies precisely.

Harris [16] made a brief review on data windows and stated their influence on the detection of harmonic signals in the presence of harmonic interference and broad-band noise. It laid down the guide for performance parameters and evaluation for various window functions on the basis of which window functions are compared.

Discrete fourier transform (DFT) is a parameter for energy detector and thus the selection of window has small impact on worst case performance. Classic windows were examined which satisfy the condition of the optimality. The windows functions which are called good windows functions exhibit values for equivalent noise bandwidth and 3-db bandwidth between 4 and 5.5 percent. Window performance in spectral inspection is also apt to shading for array processing of spatial sampled data [16].

Nuttal *et al.* [17] derived windows with better sidelobes and optimal behavior. He improved plots of Harris's windows and also obtained windows with optimal operation under varying constraints. When interference appears with the desired signal, its effect is reduced by selecting windows with low sidelobe and high fall off rate sidelobes. The first sidelobe should be small in close-by interference rejection, while high fall off rate is required in distant interference rejection.

The reader can select a window according to requirements on the basis of nearby sidelobes and faraway sidelobes. The kind of window selected here embellish various alternative choices, relying on the application of interest, and range from -31db to -98db for the first peak sidelobe and 6 db/octave to 42 db/octave for sidelobe fall off rate [17].

2.3 WAVELET TRANSFORM IN ECG

In biomedical signal processing, WT has proved to be very helpful and useful in the interpretation of signals specifically ECG. In this review, WT rising role in ECG is scrutinized in detail.

Singh *et al.* [18] focused on the selection of an optimal wavelet basis function applied to denoising of an ECG signal. The selected basis function should not be optimal only in terms of root mean square error (RMSE), but also it preserves the peaks of the ECG signal, which contains valuable physiological information for diagnostic purpose.

Noise always degrades the ECG signal and its removal from ECG is complicated task as ECG is non-stationary signal. **Haddadi** *et al.* [19] stated that DWT is very efficient in removing two major source of noises i.e. baseline wandering and power line interference. The results are validated on the waveforms obtained from MIT-BIH databases. DWT is efficient in denoising ECG as it does not change morphology of waveform as amplitudes and intervals of waves within ECG are not altered. It can be integrated with any automatic ECG analysis system.

Sabherwal [20] proposed method for to find R peaks and total beats in the raw data of ECG. Firstly ECG waveform was generated, then waveform is denoised by eliminating the wavelet coefficients at higher scales. Further R-peak is found in QRS complex and in the last beat rate is calculated. Db4 was used as mother wavelets and the highest value of the approximation coefficients at level 4 was used as significant point. R-R interval indicates the irregularity of the heart beat.

Banerjee *et al.* [21] suggested a feature extraction technique based on DWT in the QT segment of electrocardiograph waveform. The first and foremost step was to de-noise the signal using DWT by neglecting the coefficients corresponding to the noise components. R-peak was identified using an adaptive thresholding along with a multiresolution approach. Further Q, S-wave, QRS onset and offset points were located. Finally, additional feature like T-wave was also determined.

By pinpointing the baseline of ECG signal, height of R, Q, S, T-wave were calculated. The power spectra of various segments of ECG beat form the foundation of reconstruction scales. This discards noise, artifacts and interference of other segments of the signal while extracting a specific complex. ECG classifier can be proposed in the future to categorize ECG waveform into different kinds of abnormalities [21].

QRS complex is the most important component in the ECG. Thus QRS detector should be able to find variety of various QRS morphology. **Zidelmal** *et al.* [22] examined that the wavelet detail coefficients are very effective for the recognition of morphologies in QRS complex of ECG. As the energy level of the normal and abnormal ECG beat vary, so power spectrum of QRS complex forms the basis for the method. Thus it helps to distinguish between beats.

Based on QRS complex, R-peak identification algorithm is suggested and tested with MIT-BIH arrhythmia database. It is stated that normal and abnormal beats are pertinent, thus enhancing the use of DWT in energy levels. The details of d4 and d5 in taken into consideration for both the beats while the artifacts, T and P-wave are attenuated thus discarding the need of preprocessing. The algorithm is simple and less time consuming as many of beats are identified with the initial threshold [22].

2.4 CLASSIFICATION

Classification is the way of identifying different objects into predefined categorizes or classes based on the observation of the training set.

Hen *et al.* [23] demonstrated a novel approach to indicate the feasibility of having a patient-adaptable ECG beat classification technique. It presented a “mixture-of-experts” (MOE) method to embellish ECG classifier to improve their operation and to provide better health care. Large ECG database of many patients were given as input to a small classifier which is further collaborated with global classifier. It can easily be adjusted with automatic ECG analyzer. It would ultimately promote decentralized remote patient monitoring systems. Thus it has immense potential for patient adaption.

Osowski *et al.* [24] presented a new technique employing fuzzy neural network and features from higher order statistics. In the feature selection, cumulants of second, third and fourth orders are used. This hybrid model has fuzzy self-organization sub network and is cascaded with multilayer perceptron acting as final classifier. The study proved that the technique has practical application in recognition and classification of various heart beats. The confirmed good efficiency of the proposed method and the classification of normal and different beats represented arrhythmia had been done with a fine accuracy. Moreover, the suggested approach is simple, fast performance and good recognition rate.

Pandit *et al.* [25] represented an abnormal ECG beat detection technique with the improvement on feature extraction having medical information of normal and abnormal beats. A set of 16 features were selected for the classification. Features have information about intervals, shape, positions, duration and amplitudes Q, R, S, T and P-wave. Classifiers like NN, SVM, RF, rpart, ada and K-NN were employed for abnormality detection. The proposed feature set with generated extra features together contributed to greater accuracy of abnormality recognition.

Chazal *et al.* [26] presented the method that automatically classifies the beats into five classes. The raw data of 22 recordings was obtained from MIT-BIH arrhythmia with each having near about 50,000 beats. The dataset was divided into two parts. First part was used to choose a classifier configuration. The performance of twelve classifiers configuration was studied and the best one is selected. Features sets from the chosen configuration were based on morphology, heartbeat and R-R intervals. All the configurations adopted a supervised learning. The second dataset provided the performance assessment of the chosen configuration. This assessment provided sensitivity and a positive predicitivity of 75.9% and 38.5%. These results were an improvement on the earlier reported results for automated classification.

2.5 GAPS IN THE STUDY

From the literature reported above following gaps have been observed:

- All the above methods either used time domain features or transforms that provide fixed resolution where hidden complexities and subtle changes in the ECG beats are not clearly deciphered.
- The generalization of these methods was not tested on large data sets as they were tested on limited datasets.

CHAPTER 3

ECG SIGNAL DENOISING USING WAVELET TRANSFORM

ELECTROCARDIOGRAM is the P-QRS-T wave having sinus rhythm throughout, representing the cardiovascular activity. Information enshrouded in ECG is beneficial in determination and prognosis of the diseases anguishing the heart. Generally, ECG have noise signals within it. So signal processing transforms or techniques should ensure the elimination of noise as well as to preserve the characteristics peaks of the ECG wave.

In this chapter, a brief study of heart, generation of ECG wave and digital processing techniques in denoising the ECG wave and obtaining a clean ECG for further analysis is done.

3.1 ANATOMY OF HUMAN HEART

The heart is an organ, almost the size of our fist, which pumps the oxygenated blood to all parts of the body and deoxygenated blood to the lungs. It has four chambers as shown in Fig. 3.1: two atria on the top are smaller ones chambers and the ventricles compromises the bottom two chambers of the heart which are larger in size. The chambers which receive the blood from other parts of the body are named as atria whereas the chambers which circulate or send the blood from heart to other parts of the body are called as ventricles.

The one-way valves lie between the chambers: tricuspid valve, pulmonic valve [27], mitral valve and aortic valve. The valves enable the flow of the blood in the right direction. Pulmonary valve directs the blood to lungs from heart [27, 28] whereas aortic valve directs the blood from heart to body circulation system. The mitral valve divides left atrium and ventricle and the tricuspid valve partition right atrium and ventricle.

Human heart never stops thus it constantly keeps distributing oxygen to all body parts. A cycle work as: deoxygenated blood from superior vena cava is brought into right atrium, when the atrium contracts the blood is pumped to right ventricle.

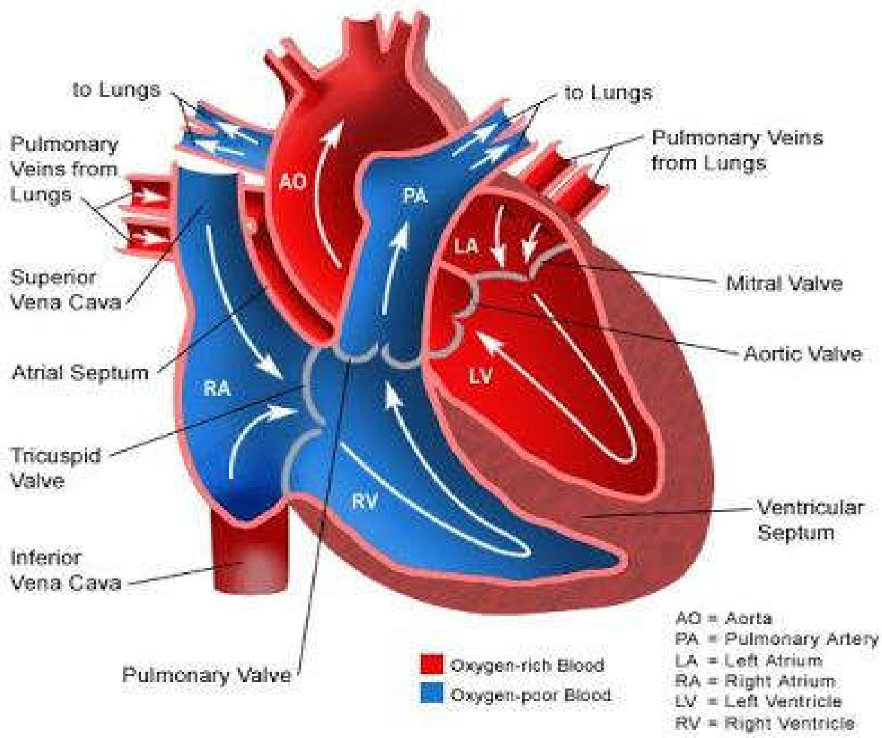


Fig. 3.1 Human Heart [27]

The right ventricle directs the blood to pulmonary artery to lungs where carbon dioxide is replaced with oxygen. Oxygenated blood from lungs return to left atrium. When atrium contracts, blood is pumped to left ventricles [27]. The blood from left ventricle goes to the circulation system of the body through aorta. The activation period when heart fills with the blood is called depolarization and relaxation or recovery stage is named as repolarization from electrical point of view.

In the human heart, there are specialized fibers which allow rapid transmission of electrical impulses across the muscle, signaling them to contract called myocardial. To maximize the force of contraction, a uniform sequence is followed by heart: the atria and then ventricles contracts [27, 28] as clearly depicted in Fig. 3.2.Thus allowing the blood to completely direct it to next destination. The impulse responsible for contraction is originated in sinoatrial node (SA), then the tissue channels the impulse through atrioventricular node (AV) situated between two sets of chambers. This area allows slower transmission of impulse to ventricles, [27] thus permitting atria to empty into ventricle before contraction and directing blood to lungs or body.

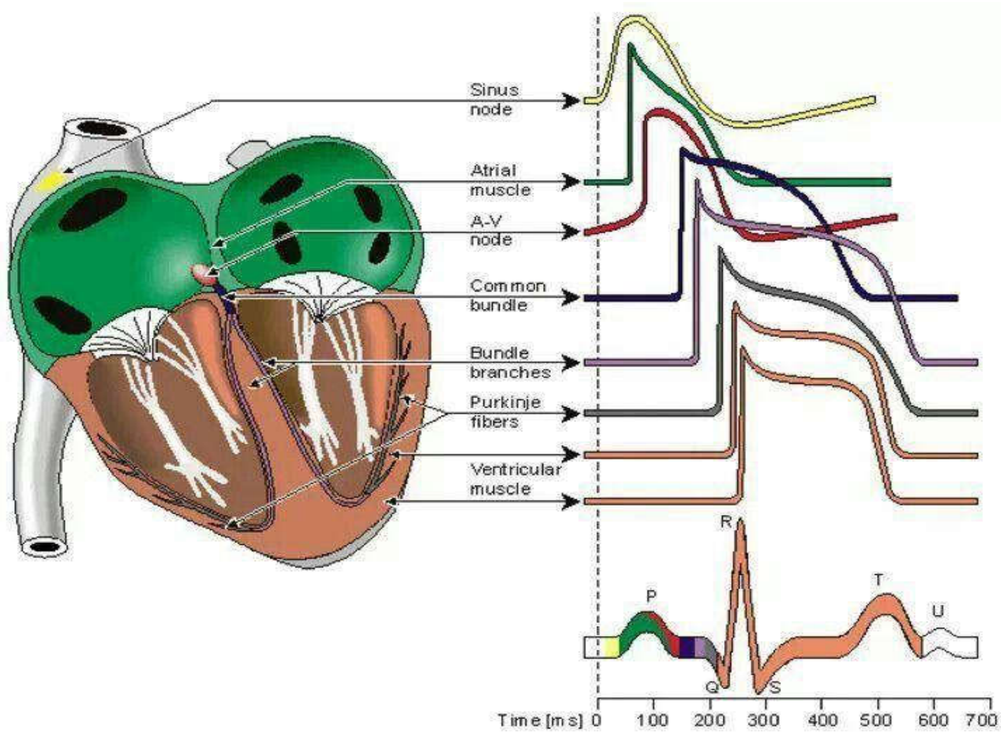


Fig. 3.2 Propagation of ECG wave [2]

AV passes the impulse through atrioventricular bundle or the bundle of His. This bundle bifurcates itself through the ventricles into two parts: the bundle branches and Purkinje fibers. Thus the muscles of ventricles are contracted, maximizing the force of ejection.

3.2 ECG WAVE

As the impulse propagates the heart, so measuring the electrical activity of the heart by placing the electrodes on patients at specific places generates a particular waveform that provide us the information about the current situation of the heart. The normal ECG beat consists of three main parameters [28] as clearly depicted in Fig. 3.3:

- **P-wave** corresponds to impulse across atria to the AV node. It has amplitude of 0.25 mV.

- **QRS complex** represents the electrical impulse as it propagates across the ventricles. R-peak has amplitude of about 1.6mV, Q and S-wave has amplitude 25% of the R wave.
- **T-wave** corresponds to recovery or repolarization of the ventricles having amplitude of about 0.1-0.5 mV.

Thus observing the shape, regularity and time intervals between various waves in ECG as shown in Fig 3.3 [29], we can learn about the conduction system.

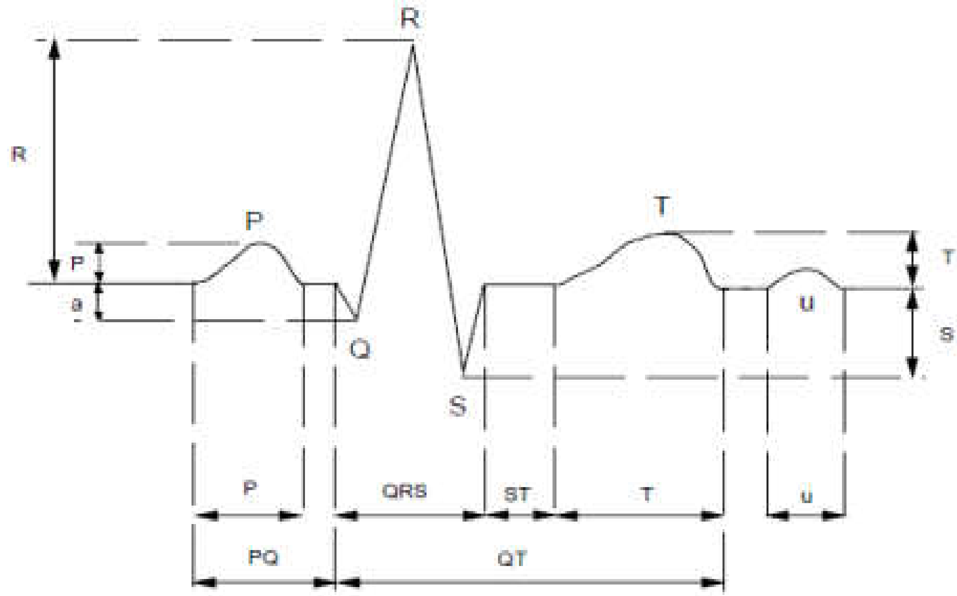


Fig 3.3 Normal ECG [29]

The main characteristics of normal ECG beat are:

- **R-R interval**: It is the time-interval between two adjacent R-peaks. This time-interval is about 0.12-0.20 seconds.
- **QRS interval**: It is computed from the start of the first wave of the QRS to the last wave in the QRS complex. The normal ECG beat has QRS complex duration about 0.04-0.12 seconds.
- **ST interval**: It appears when the heart contracts and the cell membranes are depolarized but comparatively stable. It has duration of about 0.05-0.15 seconds.

The various other time-intervals of normal ECG waveform are enlisted below in the Table 3.1

FEATURES	TIME (sec)
RR	0.6-1
QRS	Upto 0.12
PR	0.12-0.20
ST	0.05-0.17

Table 3.1 Time intervals of normal ECG [29, 2016]

Thus each healthy ECG beat has sinus rhythm which compromises atrial depolarization which results in P-wave, QRS complex consists of ventricular depolarization and T-wave is an outcome of the swift repolarization of ventricles.

3.3 ARTIFACTS IN ECG

ECG beat is superimposed with noise which makes its clinical analysis difficult. Mainly the artifacts are due to unstable and unpredictable analyzing environment, spurious signal or spike from nearby equipment, muscle movement and respiration are common factors for noise in ECG [30].The prominent and common noises in waveform are:

- **Persistent noises**:- These noises occur from all the leads having identical temporal distribution but different intensity level. The various persistent noises are enlisted below:
  - **i.** ***Baseline wanders**:* **-** It is a low frequency mainly below 1 Hz disturbance mostly caused by muscle movement, during respiration or exercises. The range for baseline wander can be wider during exercises. Basically, in baseline wandering, isoelectric line changes its position. The elimination of the artifacts is necessary for faithful visual examination of the beat. The use of normal high pass filter can distort the ECG wave as its frequency varies with time, so wavelet transform is used [18, 30].
  - **ii.** ***Power line interference:* -** It is indicated by an impulse harmonics of 60 Hz or 50 Hz. It will also occur at integral multiples of the fundamental frequency. DWT proved better than a notch filter of 60/50 Hz [18].
  - **iii.** ***Electromyography noise (EMG)**:-* It is mainly caused by contraction of muscles besides heart muscles. Thus this contraction in the proximity of the electrode

generates depolarization and polarization [30] of waves and these waves are picked up by ECG. The magnitude of EMG is random in nature and is modeled by Gaussian distribution function. The mean of this noise is supposed to be zero whereas variance is dependent on environmental variables. This noise is commonly observed in subjects with unstoppable shiver, paralyzed persons and children.

- **Burst noises:-** This noise is categorized as white Gaussian noise which occurs for short duration and their frequency range is not well defined. The different types of burst noises are given below:

  i. ***Electrode popup noise*:-** The abrupt change in ECG wave amplitude and low frequency baseline due to change in location of heart with respect to electrode causes electrode popup noise [31]. The skin-impedance is the main cause for baseline. Thus abrupt variation in baseline causes instant baseline transients which diminish exponentially to ECG baseline value. It may appear once or in succession. Thus the magnitude of initial transition and time of decay are main parameters for this noise.

  ii. ***Patient electrode motion artifact*:-** The variation in baseline due to electrode motion causes electrode motion artifact. Mainly respiration, movements causes artifacts motion. It depends on electrode properties, skin impedance [30] and movement of patient.

  iii. ***Instrumentation noise*:-** It is caused by equipments or instruments like electrode probe, cables, Analog-to-Digital convertor, etc used in ECG diagnosis [30]. It cannot be eradicated but is decreased by selection of appropriate circuit. Two major noises are: thermal noise and flicker noise. The random oscillation of electrons caused by thermal disturbance is called as thermal noise. However, at low frequency charge trapped in interface of two materials is called flicker noise. It is noticeable as its amplitude is in millivolts.

Thus signal processing and analyzes is required in ECG to make its visual interpretation easy thus deciphering its hidden information which is helpful in further steps like feature extraction and classification. The conventional methods for ECG processing and analysis is discussed in section 3.3.1.

3.3.1 Conventional Method for ECG Signal Processing and Analyzes

The conventional ECG processing includes [32]: pre-processing, band pass filtering, feature extraction and classification as shown in flow chart in Fig. 3.4

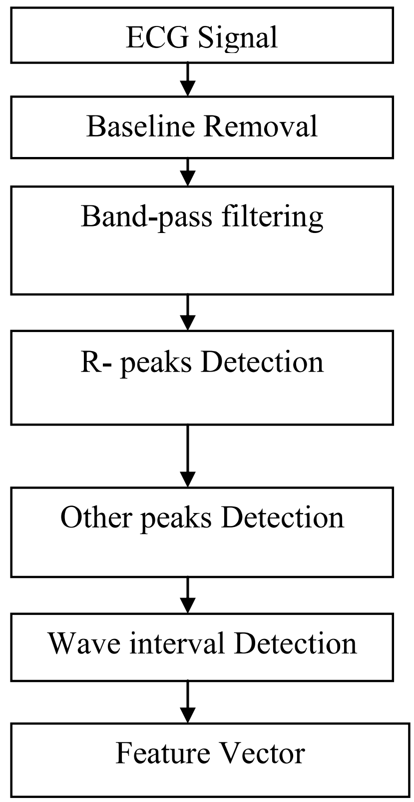


Fig. 3.4 Flow chart of ECG processing and classification [32]

The signal is firstly procured from Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) arrhythmia then pre-processing steps like baseline wandering and band pass filtering are performed before subjecting it to feature extraction methods. The feature vector includes the features extracted during feature extraction and it forms the basis for the classification of beats into healthy and unhealthy ECG beat.

Thus conventional methods did not employ efficient digital processing technique which can efficiently remove the noise and other artifacts from procured ECG which are not completely removed by digital band pass filtering and making the study of ECG wave easy for diagnosis purposes.

3.4 WAVELET

Wavelet was initially proposed by J. Morlet and A. Grossman along with Y. Meyer. At earlier stages, it was pure mathematics until two researchers Daubechies [33, 35] and Mallat draw correlation between wavelets and digital signal processing. From then, it was used in various fields and application and it was suggested as an alternative to Fourier transform (FT) and short time fourier transform (STFT). Thus unlike FT and STFT, the interpretation of non stationary signals using wavelet transform yields better results. Wavelet analysis is able to reveal various aspects of the signal very precisely like miss, such as trends, breakdown points, discontinuities, etc.

A wavelet is a small wave as shown in Fig. 3.5 which is oscillatory nature, tends to zero has time approaches infinity and is localized on the time axis [33, 34]. Wavelet has vast area of application from climate estimation, image compression and seismic and medical signal interpretation. In the 1990s the scientists and the researcher's community as reflected their interest in WT and its implementation increased and the different application of wavelet transform emerged.

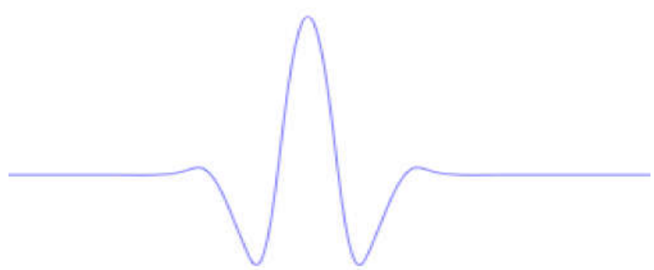


Fig. 3.5 A typical Wave [33]

The wavelet is selected depending on the type of the signal and the application for which it is analyzed. The wavelet transform is evaluated for different scales and locations of signals and it is achieved in a continuous way for CWT or in discrete steps using DWT [34].

A function is called wavelet if it satisfies the below condition [33, 34, 35]:

- Finite energy.

$$E = \int_{-\infty}^{\infty} \varphi(t) dt < \infty \quad (3.1)$$

A wavelet should have finite energy (E).

- It should have no zero frequency components.

$$C_{\varphi} = \int_0^{\infty} \frac{|\varphi(f)|^2}{f} df < \infty \tag{3.2}$$

The mean of the wavelet $\varphi(t)$ should be zero. This is called admissibility constant.

- For complex wavelets, FT $\varphi(f)$ should be real and vanish for negative frequencies.

Types of the Wavelets family:

- **Haar wavelet**: It is the first and simplest wavelet as shown in Fig. 3.6. The mathematical function of haar wavelet is:

$$\varphi(t) = \begin{cases} 1 & 0 \leq t < 1/2 \\ -1 & 1/2 \leq t < 1 \\ 0 & otherwise \end{cases} \tag{3.3}$$

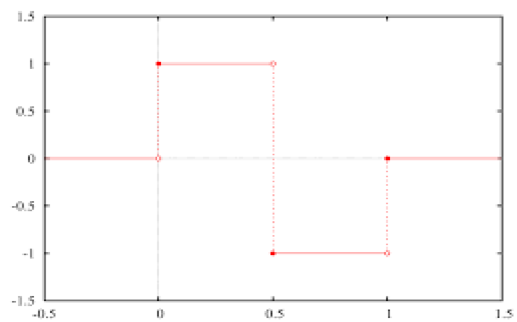


Fig. 3.6 Haar Wavelet [33]

As it is discontinuous, so it is not differentiable but it is very helpful in the study of signal with abrupt transition like detecting of tool failure in machines

- **Morlet**: Mathematically, it is composed of complex exponential multiplied by Gaussian window. It is helpful in music transcription as it captures the repeating an alternating notes of small bursts with exact beginning and end time. Morlet wavelet is shown in Fig. 3.7

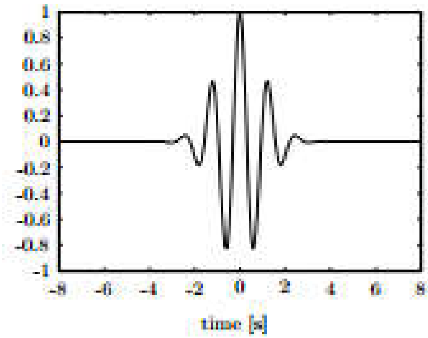


Fig. 3.7 Morlet wavelet [33]

- **Daubechies wavelets**: They are family of orthogonal wavelets which are characterized by vanishing moments. The index number N in Daubechies (db) indicates number of N coefficients. For example, db4 has two vanishing moments and so on. The commonly used Daubechies wavelets are db1-db10. The vanishing moments limit [34, 35] the wavelet ability to represent the information in the signal.

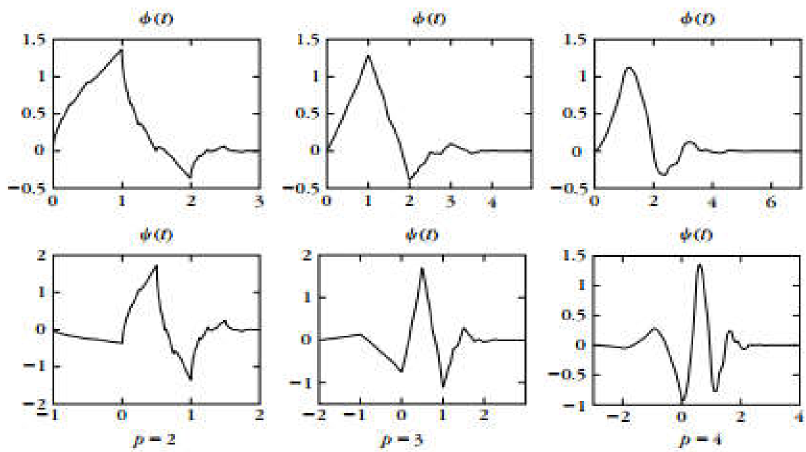


Fig 3.8 Daubechies wavelets [35]

In Fig. 3.8, p represents vanishing moments, $\emptyset(t)$ and $\varphi(t)$ [34] represent scaling function and mother wavelet function.

- **Biorthogonal wavelet**: It is non orthogonal wavelet which has invertible wavelet transform. Designing biorthogonal wavelets allows more degrees of freedom. It has two scaling functions which give different multiresolution analyses and correspondingly two different wavelet functions. The number M and N [33] of coefficients may differ in scaling sequence a, a' but they must satisfy the following biorthogonality criteria:

$$\sum_{n\in Z} a_n a'_{n+2m} = 2.\delta_{m,0} \quad (3.4)$$

- **Coiflets**: They are discrete wavelets modeled by Daubechies [34] to have scaling function with vanishing moments and minimum support size. This type of wavelet is nearly symmetric as shown in Fig. 3.9.

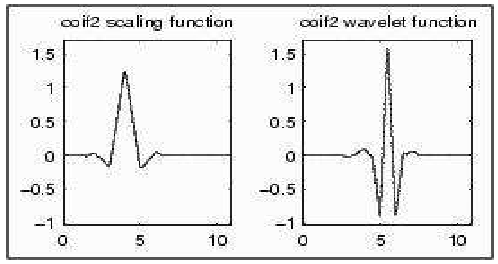


Fig 3.9 Coiflets wavelets [34]

- **Symlets**: They are designed to more symmetric than Daubechies [34] as clearly depicted in Fig. 3.10.

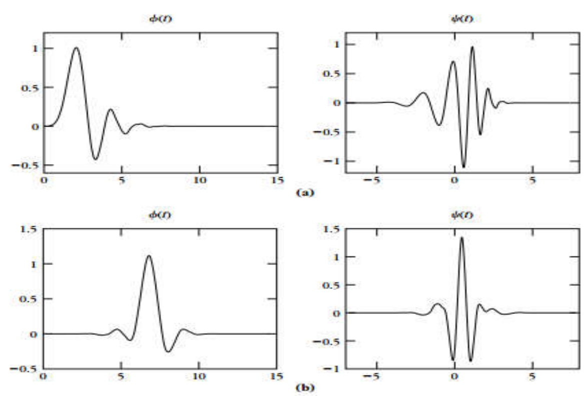


Fig 3.10 (a) Daubechies wavelet (b) symlet wavelet [34]

3.4.1 Continuous Wavelet Transform (CWT)

The continuous wavelet transform is a convolution of the wavelet function with the signal mathematically [33]. It is defined as [33, 34, 35].

$$X_{WT}(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t)\varphi^*(\frac{t-\tau}{s})\, dt \tag{3.5}$$

The transformed $X_{WT}(\tau, s)$ is a function of translation τ and scale s parameters and $\varphi(t)$ indicates the mother wavelet and $*$ complex conjugate used in complex wavelet. The wavelet coefficient $1/\sqrt{|s|}$ is divided at every scale to normalize the energy of the signal ensuring same energy at every scale.

In (3.5) s is the dilation factor [35] that maintains or controls the width of the wavelet and τ is a translation parameter controlling the position of the wavelet. Dilation or scaling is either stretching or compressing the wavelet. If $|s| > 1$ then wavelet is stretched or compressing it if $|s| < 1$ whereas in translation it means shifting its position in time.

The frequency domain information is given by s in (3.5) and τ gives the time domain position of the wavelet. Thus WT maps the original signal to a function of τ and s, giving simultaneous information of time and frequency.

CWT can be accomplished in two ways either by changing the location or scale. The wavelet coefficient $X_{WT}(\tau, s)$ is related to a scale and a point in time domain. Similar to FT and STFT, WT also has inverse transformation known as inverse continuous wavelet transform (ICWT) defined as:

$$x(t) = \frac{1}{C_\varphi^2} \iint_{-\infty}^{\infty} X_{WT}(\tau, s) \frac{1}{s^2} \varphi\left(\frac{t-\tau}{s}\right) d\tau ds \tag{3.6}$$

The admissibility constant C_φ should satisfy the wavelet constraint.

The scale is indirectly proportional to the frequency thus large scale provides global information whereas large scale indicates the detail information of the signal.

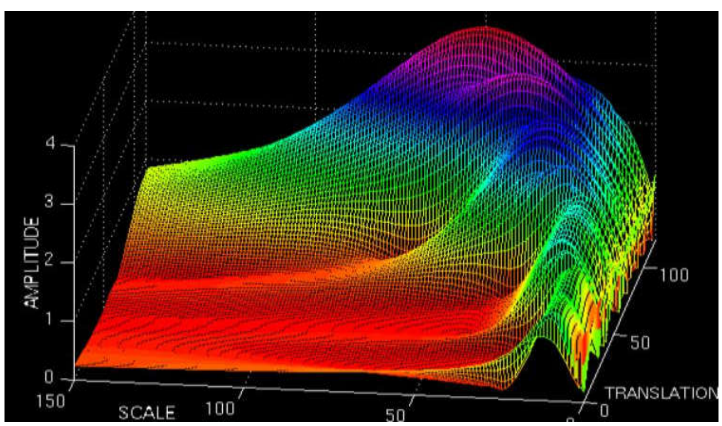


Fig 3.11 Continuous Wavelet Transform [33]

Fig 3.11 shows CWT of good frequency resolution and poor time resolution. The CWT contracts and dilates the wavelet functions to give the time-frequency representation.

3.4.2 Discrete Wavelet Transform (DWT)

In digital computers or digital processing, discrete wavelet transform is used. Sampling the CWT on the dyadic grid as gives the DWT. The scale parameter is sampled on a logarithmic scale on a dyadic grid. It is the straightforward and faithful discretization methods for practical application and it helps in the construction of an orthogonal wavelet basis.

DWT can be implemented using sub-band [34] decomposition using digital filter. Thus it can be realized using tree structure as shown in Fig. 3.12. The signal is passed through low pass $h(n)$, then down sampled by a factor of two. The high pass filter is obtained from the low pass filter as:

$$g(L-1-n) = (-1)^n h(n) \tag{3.7}$$

In (3.11) L is the length of the filter. The two filters $h(n)$ and $g(n)$ are called quadrature mirror filters.

At each stage in tree structure as shown in Fig. 3.12 the signal is bifurcated into two parts: high and low frequency components. These two components contain redundant frequency components after filtering, thus it is subsample by a factor of two [33, 34, 35] without losing any information

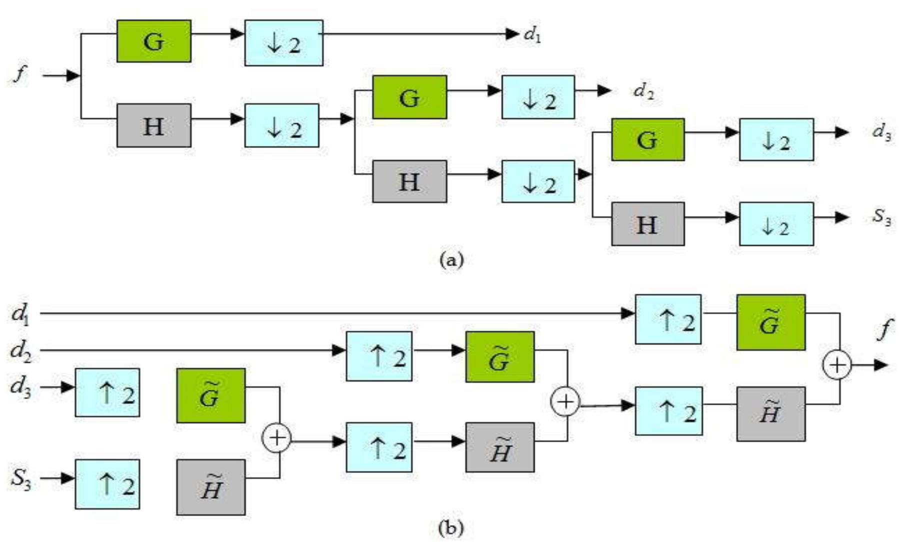


Fig 3.12 (a) DWT (b) IDWT using filter bank [34]

If the wavelet is repeatedly dilated by a factor two, logarithmic frequency coverage [33] is shown in Fig. 3.13.

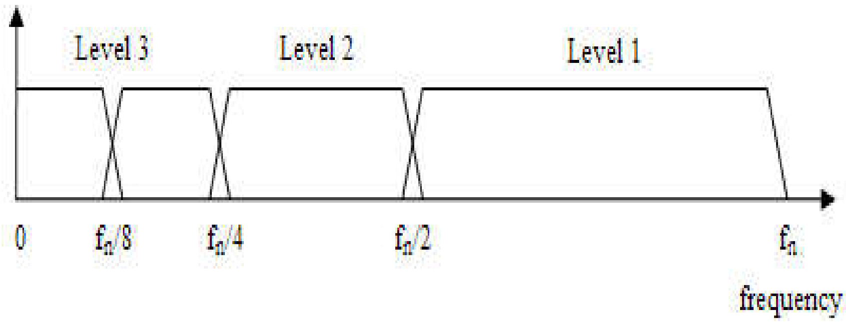


Fig 3.13 Logarithmic coverage of frequency [33]

The sub bands created by filters shown in Fig. 3.12 are a true sub sampled set of CWT. The wavelets used as the basis functions for DWT form an orthonormal set. For wavelet set $k_{a,b}(t)$, orthonormality is defined as:

$$\int k_{b,a}(t)k^{*}_{b,a}(t)dt = 1 \quad if\ b = b' and\ a = a' \tag{3.8}$$

Orthonormality implies that no redundant information is present. It also implies that any finite signal can be presented as a weighted sum of the basis functions and conversely the signal can be perfectly reconstructed from a full set of weighted functions. Thus DWT is also defined as [33, 34, 35]:

$$T_{m,n} = \int_{-\infty}^{\infty} x(t)\varphi_{m,n}(t)dt \tag{3.9}$$

DWT decomposes the signals into low and high frequency components. Low frequency components are called the approximation whereas high frequency is known as the detail. The approximation at scale m and location n is presented by:

$$S_{m,n} = \int_{-\infty}^{\infty} x(t)\emptyset_{m,n}(t)dt \tag{3.10}$$

The discrete summation is represented below:

$$x_o(t) = x_M(t) + \sum_{m=1}^{M} d_m(t) \tag{3.11}$$

where at scale M the mean approximation of signal is:

$$d_m(t) = \sum_{n=0}^{2M-m} T_{m,n}\varphi_{m,n}(t) \tag{3.12}$$

3.4.3 DWT in ECG

The DWT implementation is discussed in the above section using filter banks. In this section, DWT is applied on the ECG signal obtained from Physionet [36]. Any ECG signal from physionet like normal sinus rhythm, Supraventricular arrhythmia and so on. But here MIT-BIH arrhythmia is used. The obtained ECG is passed through filter banks until fourth level and the detail coefficients of the signal are shown in Fig. 3.14.

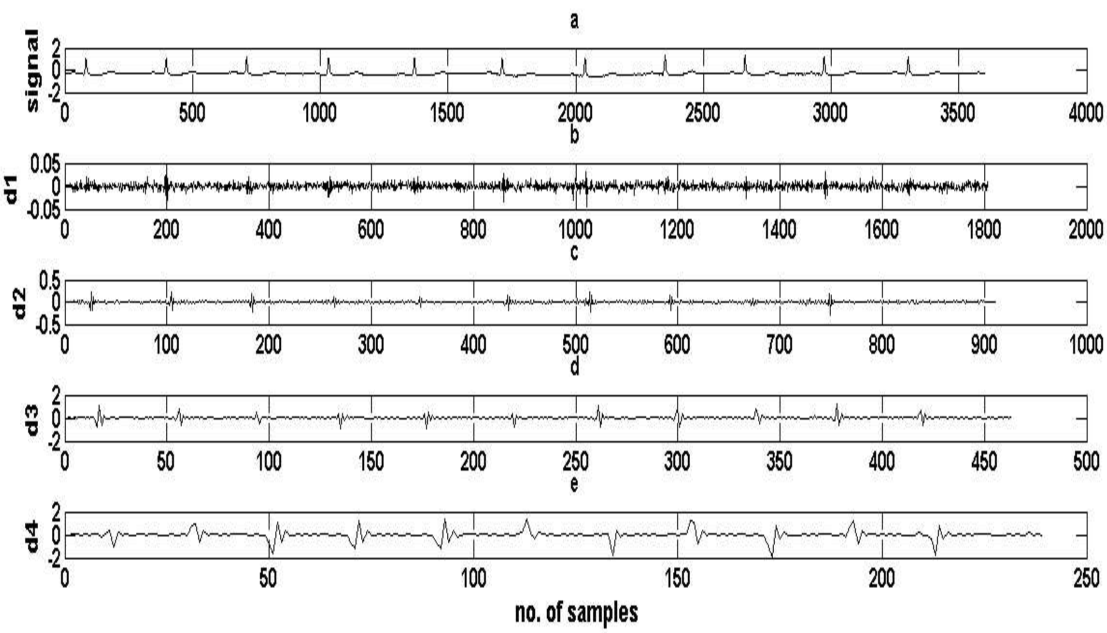


Fig. 3.14 ECG and its detail coefficients at first four level

(a) Original signal **(b)Detail coefficient of first level**

(c)Detail coefficient at second level **(d) Detail coefficient at third level**

(e) Detail coefficient at fourth level

In Fig. 3.14 (a) shows the original ECG signal of record 101 from MIT-BIH arrhythmia and subjected to denoising using Daubechies (db8). The ECG signal is sampled at 360 Hz and decomposed up to level 4 using db8.

It is clear from Fig. 3.14 that most of the noise occurs in the detail coefficients of first level (d1) shown in Fig. 3.14 (b) consisting of frequency band 90-180 Hz. To de-noise the signal d1 is equated to zero and it is not used in reconstruction of the signal. The significant sub-bands are 2nd, 3rd and 4th level detail coefficients having frequency band of 45-90, 22.5-40, 11.25-22.5 Hz shown in Fig. 3.14 (c), (d) and (e) respectively. The 4th level detail coefficients are very helpful in detecting R- peak [37].

3.4.4 Multiresolution Analysis (MRA)

The time-frequency resolution complication is caused Heisenberg's uncertainty principle [33, 34] that states that it is impossible to find the exact frequency at exact time instant but at particular frequency band Δf can be found at particular time interval Δt.

$$\Delta t \Delta f \geq \frac{1}{4\pi} \tag{3.13}$$

By using MRA approach, it is feasible to examine a signal at various frequencies with varying resolutions shown in Fig. 3.15.

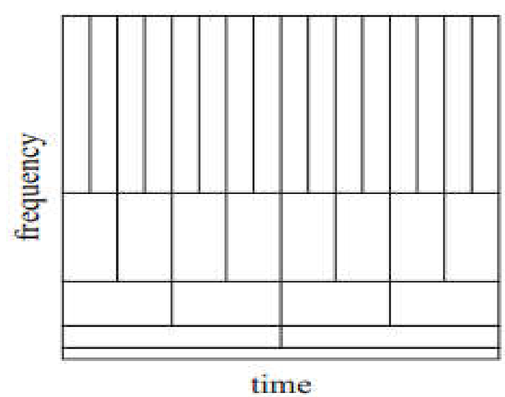


Fig. 3.15 Multiresolution time-frequency plane [33]

From Fig. 3.15, it is stated that low frequencies stays for longer duration of the signal and on the other hand high frequencies shows up as a short burst. The wavelet computes the correlation between the signal under inspection and a wavelet function. The similarity between the signal and the analyzing wavelet function [34] is calculated separately for different time intervals, resulting in a two dimensional representation.

3.5 SELECTION OF OPTIMAL WAVELET

In wavelet domain for ECG signal processing, the picking an apt mother wavelet function is of utmost importance [18, 36]. The convolution of the wavelet and the signal has high value if the wavelet is the counterpart of the signal. If they do not correlate appropriately, the transform yields low value. The suitable wavelet function will results in maximization of correlation coefficients for ECG under inspection.

Singh *et al.* [18] plotted ECG waveform, computed wavelet coefficients and then ECG is reconstructed using Haar wavelet and Daubechies wavelet. The original ECG used by Singh and reconstructed ECG plot using Haar and Daubechies wavelet is given in Fig. 3.16 and 3.17 respectively:

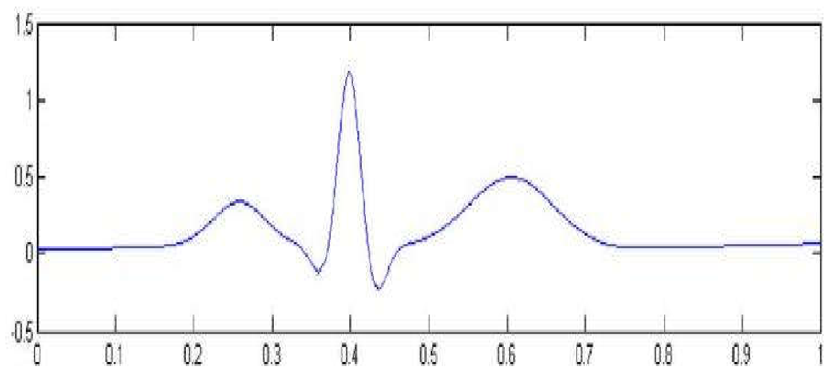


Fig. 3.16 ECG wave used by Singh [18]

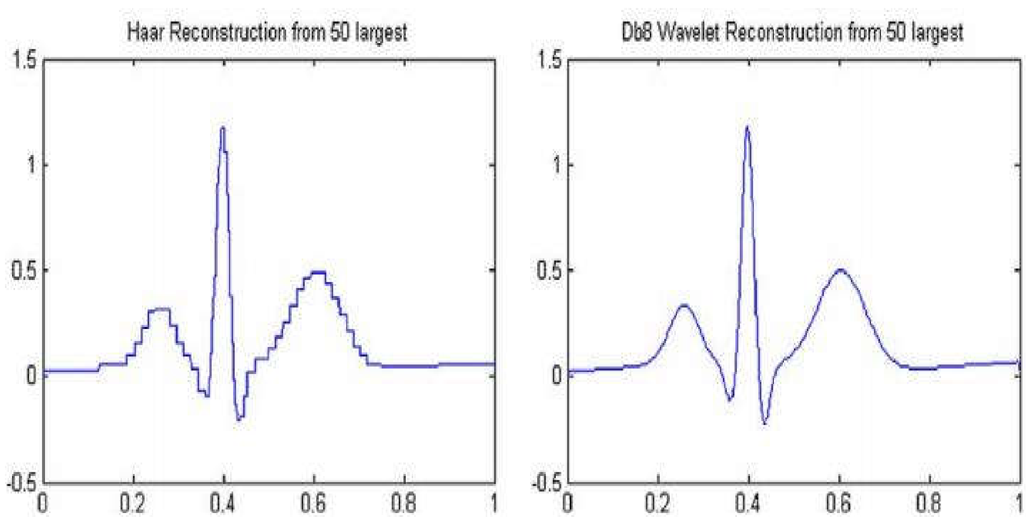


Fig. 3.17 ECG reconstruction by Haar and Daubechies Wavelet [18]

It is clear from Fig. 3.17 that Daubechies wavelet of order 8 provides better localization property than Haar wavelet. To choose the best wavelet function for ECG waveform signal processing, the following steps should be considered [18].

- Choose the basis wavelet filter from wavelet filter bank library.
- Enumerate the cross correlation between chosen wavelet and ECG signal.
- Picking the wavelet filter that maximizes the cross correlation.

Singh et al. [18] also performed the cross correlation of ECG (one cycle) with various wavelet. The results prove the aptness of Daubechies wavelet (db8) is appropriate for ECG signal processing.

3.6 Wavelet Thresholding

The reconstruction of signals in wavelet domain from noise is assumed to be smooth but it sets many coefficients to zero, thus inducing large errors [34, 38]. It is logical to presume that small coefficients can be set to zero as they are due to noise but large coefficients should be retained. There has been intensive research for removal of noise using WT in signals. There are two famous thresholding functions for signal enhancement which are soft and hard thresholding.

Hard thresholding sets coefficients equal to zero which are less than the threshold.

$$X_{hard} = \begin{cases} X \ \ if \ |X| > \tau \\ 0 \ if \ |X| < \tau \end{cases} \tag{3.14}$$

Soft thresholding sets coefficients lower than the threshold to zero and also subtracts the thresholds value from other coefficients.

$$X_{soft} = \begin{cases} sin(X)\,(|X| - \tau) \ \ if \ |X| > \tau \\ 0 \qquad\qquad\qquad\quad\ if \ |X| \le \tau \end{cases} \tag{3.15}$$

Donoho and Jonstone proposed the value for τ:

$$\tau = \sigma\sqrt{2}\, log(M)/M \tag{3.16}$$

Donoho and Jonstone [39] proposed a method on thresholding of wavelet coefficients and its reconstruction. In (3.13), $\sigma = \frac{MAD}{0.6745}$, MAD is the median of the wavelet and M is the total number of wavelet coefficients. There are different thresholding methods for calculating threshold value used in different application by researchers [18, 40].

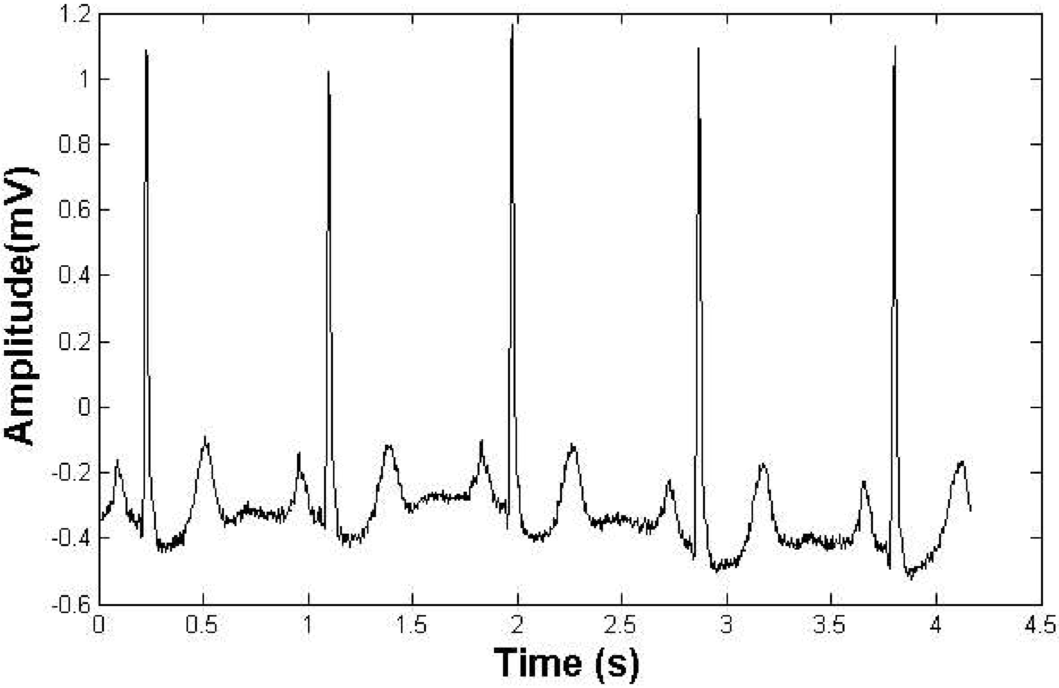
- Global thresholding: It I the fixed or global thresholding methods and is calculated as:
  $$t = \sqrt{2}\log\ (M)/M \quad (3.17)$$
  where n is the total number of wavelet coefficients. This method gives the minmax performance.
- Rigrsure: It is adaptive thresholding method based on Stein's unbiased likelihood estimator (SURE) principle and proposed by Donoho and Jonstone. Firstly, likelihood estimation using the given threshold t and then minimizing the non-likelihood t to obtain the threshold.
- Heursure: It is hybrid method of SURE and global thresholding method. If the signal to noise ratio is small, SURE gives poor threshold. In this situation global threshold yields better results.

Threshold value estimation is the crucial problem. A small threshold may yield noisy result and large threshold may cut the significant information of the signal.

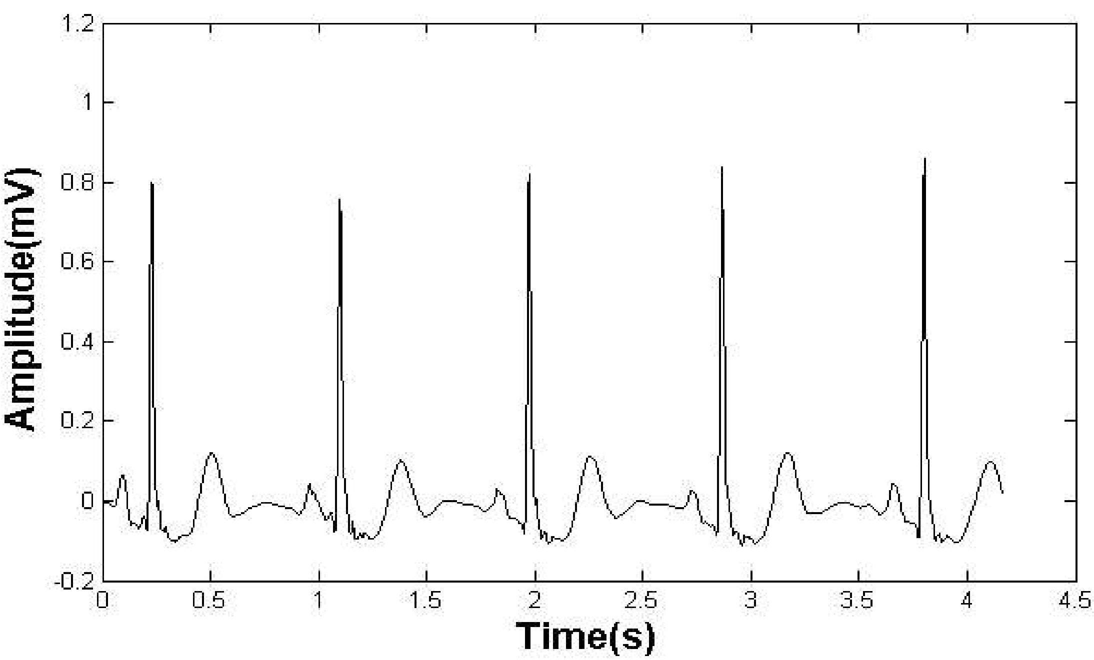
3.7 SIMULATION RESULTS OF DENOISING IN ECG AND DISCUSSION

The various records of ECG signals obtained from MIT-BIH arrhythmia database [36]. Simulations results are performed on the platform of MATLAB 2013 on a system having configuration i3 with an Intel CPU 2.10 GHz processor having 3 GB RAM.

The simulation is performed on record of 101, 103 and 106 of MIT-BIH arrhythmia. The signal obtained after subjected to pre-processing (discussed in chapter 4), wavelet denoising is performed using db8, soft thresholding and Donoho threshold value.



(a)

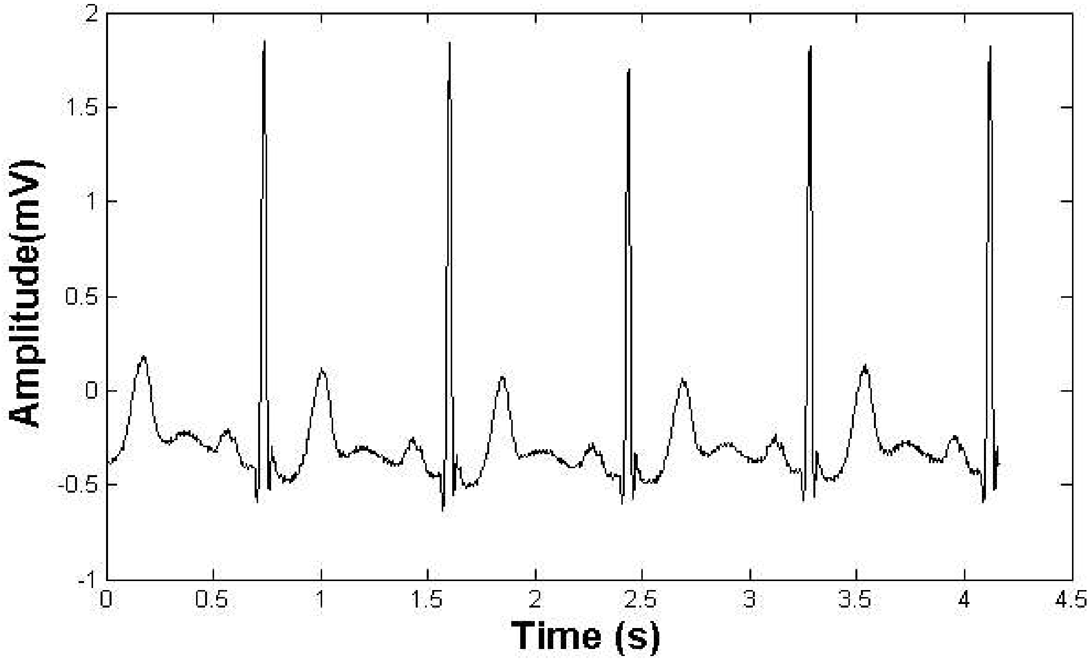


(b)

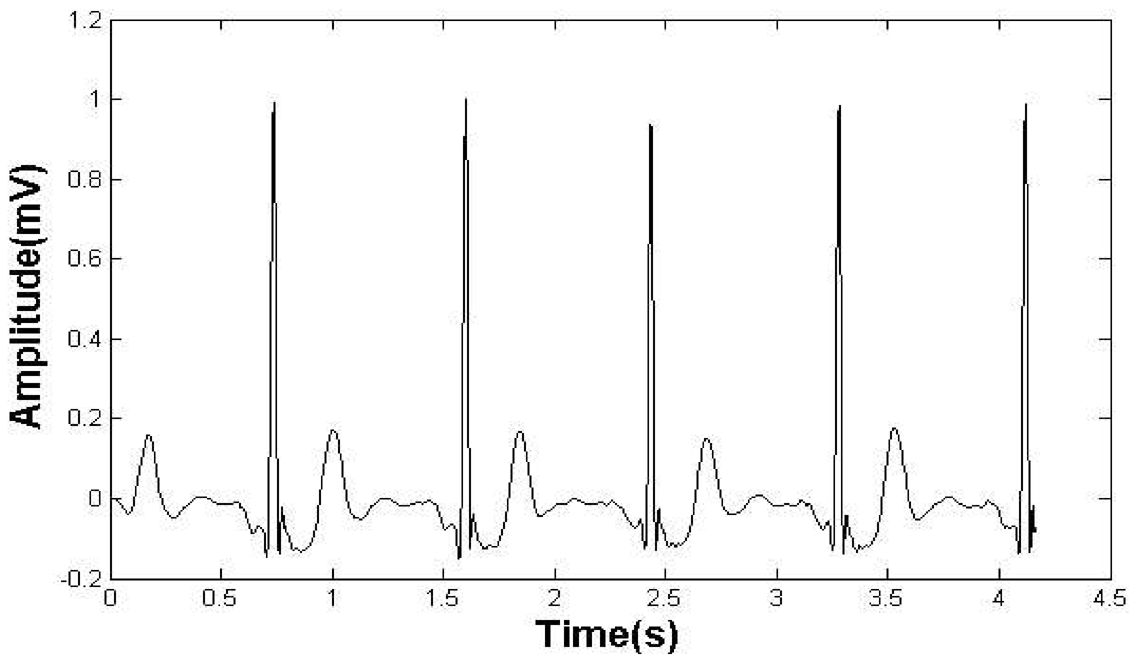
Fig. 3.18 Original signal of ECG from MIT-BIH arrhythmia of record no. 101

(a) Original signal

(b) Denoised signal



(a)

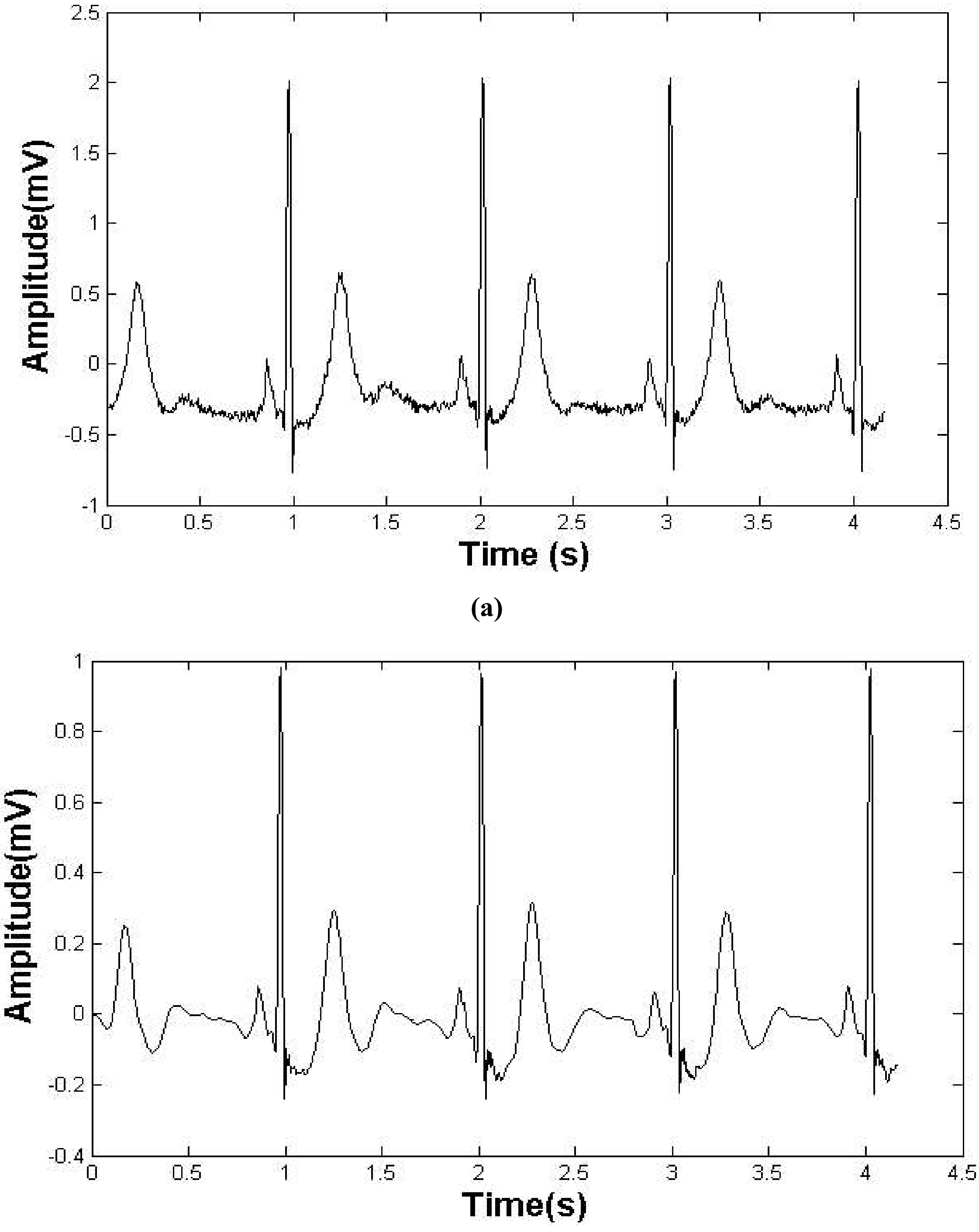


(b)

Fig. 3.19 Original signal of ECG from MIT-BIH arrhythmia of record no. 103

(a) Original signal

(b) Denoised signal



(b)

Fig. 3.20 Original signal of ECG from MIT-BIH arrhythmia of record no. 106

(a) Original signal

(b) Denoised signal

3.7.1 Discussions

Fig. 3.18 shows the original and de-noise signal of record no. 101 of MIT-BIH arrhythmia. It is clearly visible in Fig. 3.18 (a) original superimposed with the noise and moreover ECG waveform starts from below zero and in Fig. 3.18 (b) clean ECG signal is present free from all the artifacts and the baseline wandering is removed as waveform starts from zero. Beginning of the beat from zero is crucial in feature extraction like computing the amplitudes of different peaks of waveform.

Similarly denoising is performed on other records of MIT-BIH arrhythmia databases also. Records no. 103 and 106 are shown in Fig. 3.19 and Fig. 3.20.

The quantitative analysis of WT in denoising is also computed by SNR. The formula of SNR is given below:

$$SNR = \sum_{t=o}^{L-1} h(t)^2 / \sum_{t=0}^{L-1} n(t)^2 \tag{3.18}$$

where $h(t)$ is the original signal and $n(t)$ is the noise and L is the length of ECG signal. SNR is calculated by adding different levels of noise and the results are given in Table 3.2

Record no.	SNR of input signal (5db)	SNR of output signal (5db)	SNR of input signal (10db)	SNR of output signal (10db)	SNR of input signal (15db)	SNR of output signal (15db)
101	5.02	7.09	10.01	11.40	15.03	15.63
103	5	8.34	10.01	11.76	15.06	15.67
106	5.30	7.04	10.02	11.38	15.04	15.61

Table 3.2 Quantitative analysis of WT in denoising

Thus it is clearly visible in the Table 3.2 that SNR of denoised signal is greater than the raw signal. If we increase the level of noise from 5 to 15 db, WT has given better SNR than the raw signal.

CHAPTER 4

FEATURE EXTRACTION

Features in signal are the distinctive or the prominent attributes in the signal which make it distinguishable from other signals. Thus the feature extraction is the most important step which further form the feature vector and it is input to different classifier which performs classification in order to classify ECG into healthy and an unhealthy beat. Thus the proposed system has the following steps to perform classification: FIR filtering, Denoising, Feature Extraction, Classification and Performance Evaluation. The proposed model is given in Fig. 4.1. Firstly, filtering is done in order to remove other unwanted frequencies, and then signal is de-noised using wavelet transform (as discussed in chapter 3). In the next step, algorithm is applied to find temporal points such as P, R, Q, S and T and their onset points are observed to study inter waves duration. These fiducial points and various time intervals of ECG act as temporal feature for classification. The signal is decomposed using discrete wavelet transform to enumerate the detail and approximation coefficients at fourth level and they are used as morphological features. The algorithm sensitivity, positive predicitivity and error rate for determining different peaks of ECG are computed.

4.1 PREPROCESSING

According to experiment results to achieve optimal ECG filtering, two conditions should be taken care: sampling frequency and an assumption that all the unwanted frequencies are present outside 1.5-50 Hz [29]. Therefore, band pass filter is constructed by cascading FIR low pass filter of cut-off frequency (f_c) 50 Hz with FIR high pass filters with f_c 1.5 Hz.

Thus removing all unwanted frequencies below or above 1.5-50 Hz. It helps in removing low frequency artifacts like **baseline wanders** caused sue to muscle motions. Thus it ensures all essential information to be retained as ECG frequencies lie in 5-12 Hz interval. Discrete wavelet transform is applied to the output of the band pass filter to further smoothen and de-noise the signal and clean ECG as mentioned in Chapter 3.

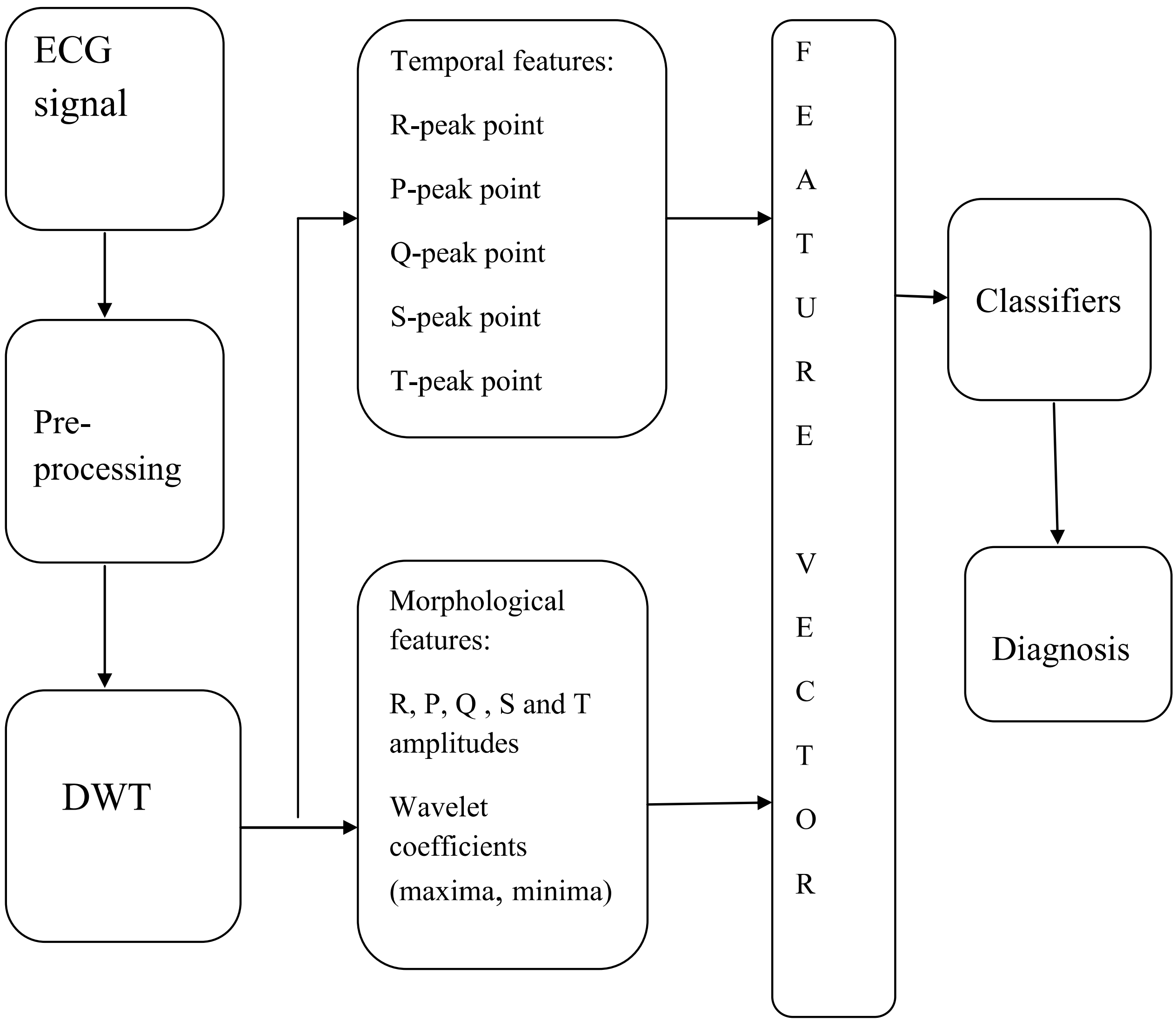


Fig 4.1 Block diagram of proposed system.

4.2 ECG FEATURES

ECG wave is discussed in brief in chapter 3 and P-QRS-T wave and various time intervals are analyzed. It is also mentioned that these waves and time intervals between these inter-waves have some specific value. If our beat falls within the prescribed parameters, it is said to be normal or healthy beat otherwise it is abnormal or unhealthy beat. Thus if a particular waveform in ECG do not follow a pre-defined shape or lie outside the prescribed intervals, it has some abnormalities and some of them are enlisted in Table 4.1.

Characteristics	Abnormality
Inverse P-wave	Dextrocardia
R-R interval<0.6	Tachycardia
R-R interval>1	Bradycardia
Tall T-wave and P-wave absent	Hyperkalemia
Inverse T-wave	Myocardial ischemia
Rapid and irregular beating	Atrial fibrillation

Table 4.1 Abnormalities in ECG signal [41, 2015]

Clinically, features are basis for the health analysis. Like, Long QT Syndrome (LQTS) is the cause for many deaths every year is identify from QT feature. The T-wave morphology is a crucial factor as inverted T wave is cause for coronary ischemia [29, 41].

Thus P-QRS-T wave amplitude and R-R, QRS, PR and ST segment (all mentioned in chapter 3) are the temporal features of the ECG signal. The wavelet coefficients also act as features of ECG wave (discussed in section 4.).

4.3 PROPOSED ALGORITHM

In the thesis, an algorithm for the detection of inter-wave intervals and peak amplitude of wave parts is proposed. The first and foremost approach is to detect R-peak accurately. In the next step other waves are detected using a local search nearby the identified R-peak. The minima before and after R-peak correspond to Q and S wave within local search interval. To determine P and T wave Soff (end point of S wave) and Qon (beginning of Q wave) are needed. The P-QRS-T determination algorithm is:

1. **R point detection** R-peak detection is the first and the most crucial step as the determination of other peaks is dependent on R-peak location. To determine R-peak, we find the locations which have amplitude more than 60% of the maximum value of the input signal. As all the unwanted noise is removed by discrete wavelet de-noising, so R-peak is detected accurately. The efficiency of R- peak detection is essential as it is used compute the heart rate interval. The difference between current R- peak location and next R-peak is called RR interval. It is the essential feature and is measured by the formula:
   $$RR(j) = R(j+1) - R(j) \tag{4.1}$$
   where $R(j)$ and $R(j+1)$ are the indexes of the present and next R-peak respectively. If any two subsequent beats lie within 0.25 seconds then it is removed from the memory as no two R-peak lie within 0.25 seconds. The R-peak detection accuracy affect the other wave peaks as their position is calculated with respect to it.
2. **S point detection:** The S-wave is the shortest length wave ranging from 6-13 samples [36], occurs at the end of the QRS. The duration of S wave is 0.016-0.036 seconds. The search interval for S and Soff is:
   $$S(j) = \min\left(location\ of\ R(j), location\ of\ R(j) + RR(j)/7\right) \tag{4.2}$$
3. **Q point detection:** It marks the starting of the QRS section, appears within 0.02-0.06 seconds before R-peak. The QR duration changes from patient to patient as if a patient has RR length 235 samples, then QR is 19 and other may have QR length of 8 samples while RR equal to 292. Thus the search interval is longer for larger RR interval.
   $$Q(j) = \min\left(location\ of\ R(j), location\ of\ R(j) - RR(j)/7\right) \tag{4.3}$$
4. **P point detection:** P- peak comes before Q-wave. PR interval is between 0.12-0.20 seconds. To detect P point, the formula used is:
   $$P(j) = \max\left(location\ of\ Q(j) - location\ of\ RR(j)/3, location\ of\ Q(j)\right) \tag{4.4}$$

5. **Pon point detection:** It is the starting point of the P-wave. It is essential for the computation of the PR duration and is calculated as given below:

   $P_{on} = \min\,(location\ of\ R(j) - RR(j)/7\,, location\ of\ P(j)$ (4.5)

6. **T point detection:** To determine T point is the most difficult task due to time varying characteristics. So, it is computed as the highest amplitude between Soff and middle of the corresponding RR interval. Thus the interval of interest is given below:

   $T(j) = \max\,(location\ of\ S(j), location\ of\ RR(j)/7)$ (4.6)

7. **Ton point detection:** It marks the beginning of the T wave. Ton is helpful in determining the polarity of the T wave: positive, negative or flat. The flat or negative T wave is the indication of serious cardiac problem, cardiac ischemia. The search interval is S-wave with addition of some offset value till appearance of T-wave and it is the minimum point in this and it is written:

   $T_{on} = \max\,(location\ of\ S_{off}(j) + \ offset, location\ of\ T(j)$ (4.7)

Summarizing the algorithm in tabular form in Table 4.2

Wave	**Start**	**End**	**Max/min**
S	Location of R	Location of RR/7	Min
Q	Location of RR/7	Location of R	Min
P	Location of RR/3	Location of Q	Max
T	Location of S	Location of RR/7	Max
Pon	Location of RR/7	Location of P	Min
Toff	Location of S + offset	Location of T	Min

Table 4.2 Proposed algorithm for detecting P-QRS-T wave

In Table 4.2 RR/7 and RR/3 denotes the particular RR interval where the wave to be determined is present. Suppose if wave to be detected is P-wave, that particular RR interval is chosen where P-wave to be determined is present.

This algorithm is implemented on 200 ECG wave of length 10 seconds obtained from various records of MIT-BIH arrhythmia, ST change, Supraventricular arrhythmia and Normal Sinus Rhythm databases obtained from Physionet [36]. Thus the features are determined on ECG signal obtained from Physionet after pre-processing and wavelet denoising.

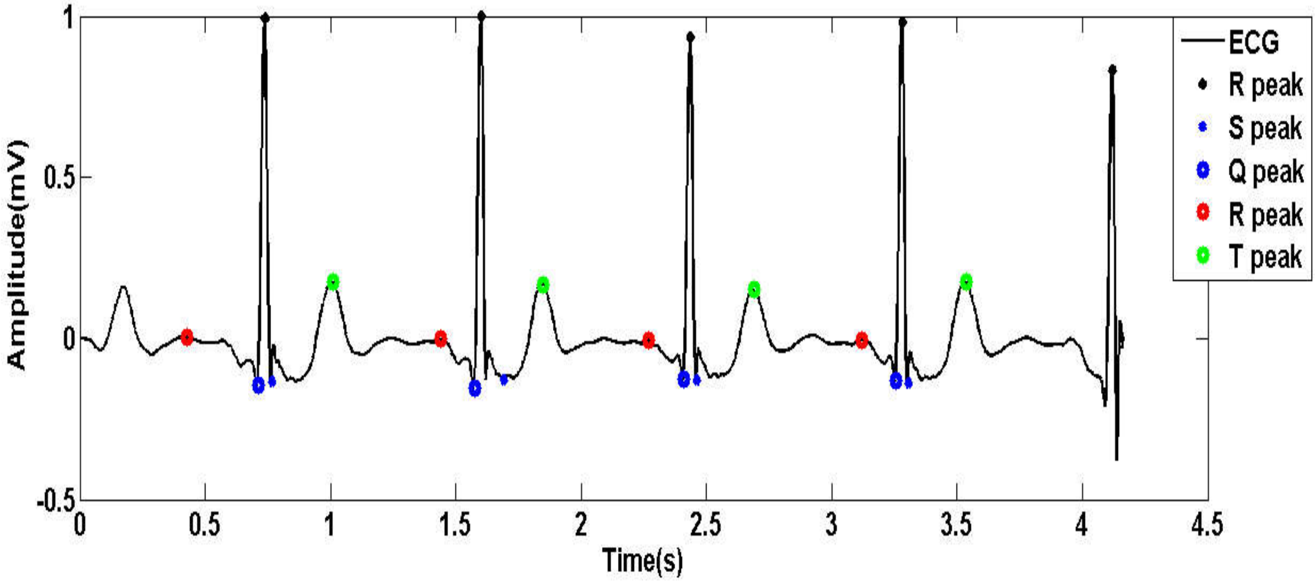
Simulations results are performed on the platform of MATLAB 2013 on a system having configuration i3 with an Intel CPU 2.10 GHz processor having 3 GB RAM.

The simulation results highlighting P-QRS-T peak of ECG wave obtained from different databases MIT-BIH arrhythmia, MIT-BIH Supraventricular arrhythmia and MIT-BIH ST change are shown in Fig. 4.2, 4.3 and 4.4 respectively. The different databases are taken to check the validity of the algorithm.

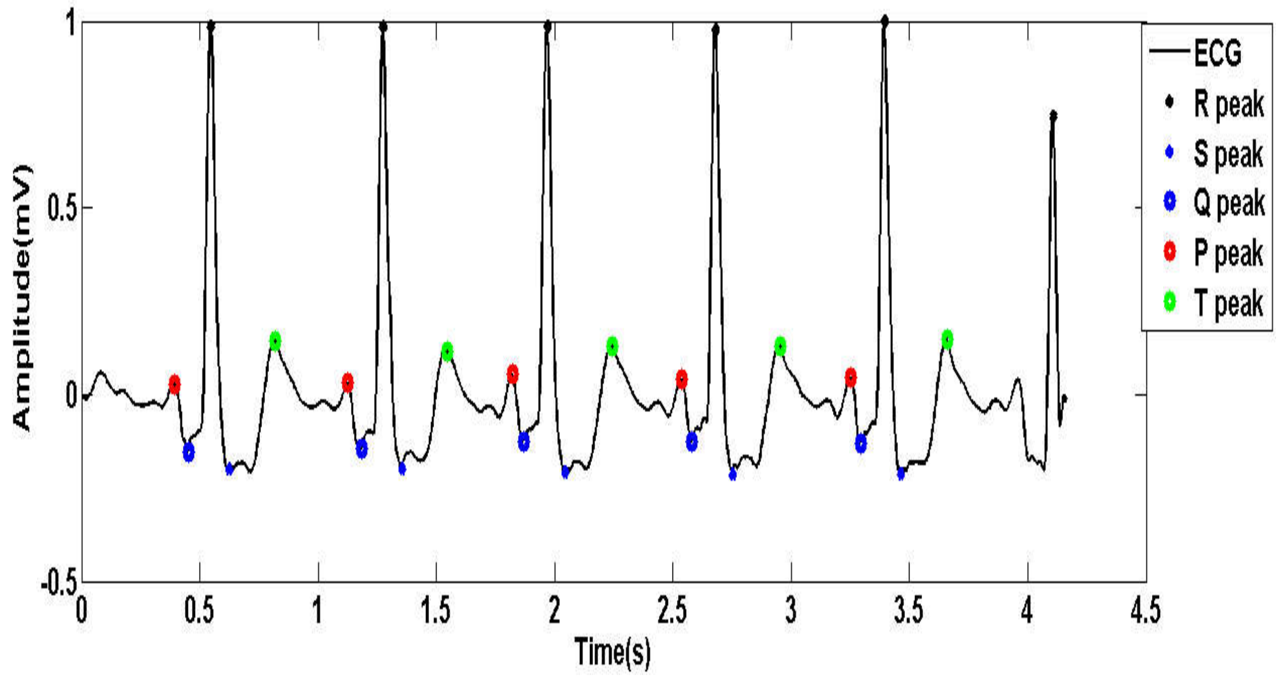
In Fig. 4.2 records no. of 103 and 105 of MIT-BIH arrhythmia are used to depict the P-QRS-T peak of ECG signal and in Fig. 4.3 record number 300 and 302 and in Fig 4.4 record number 802 and 807 are used to show the validity of the proposed algorithm on MIT-BIH ST change databases and MIT-BIH Supraventricular respectively.

In Fig. 4.5 and 4.6 onsets of P and T wave are highlighted. These two onsets are helpful in calculating ST and PR intervals which act as features in feature set. In Fig. 4.5 record number 300 and 302 from MIT-BIH ST change databases and in Fig. 4.6 record number 103 and 105 of MIT-BIH arrhythmia are used to show the onset points of P and T wave.

Similarly different records from these databases are also used. In the simulation results only few are shown.



(a)

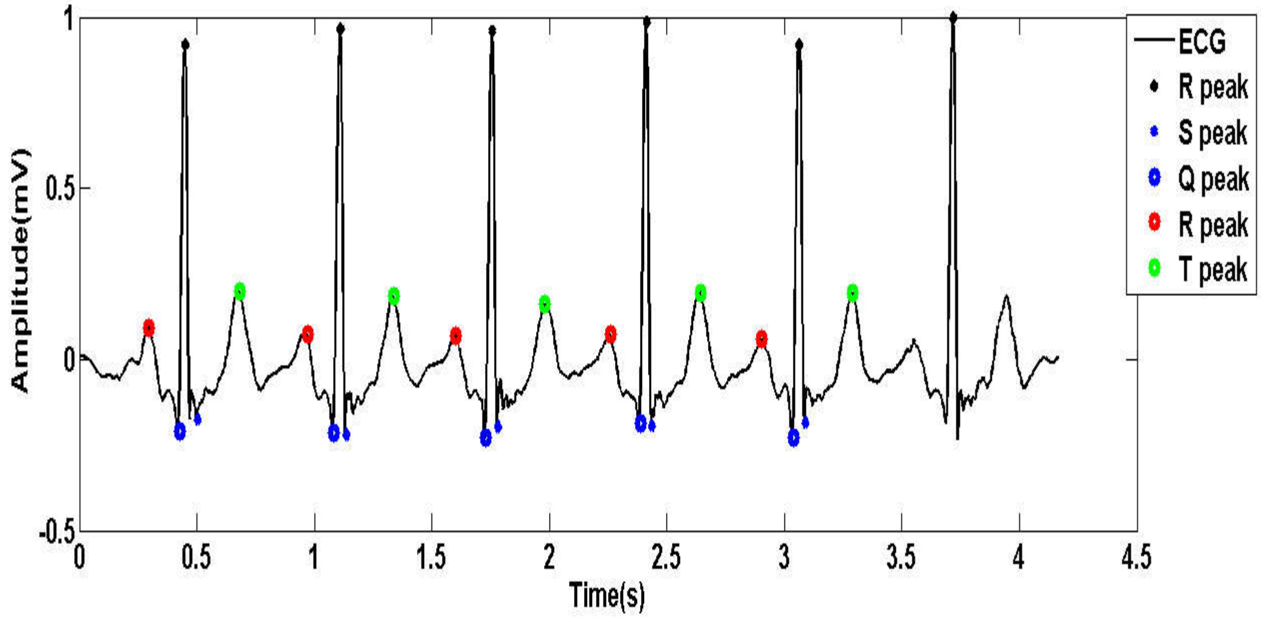


(b)

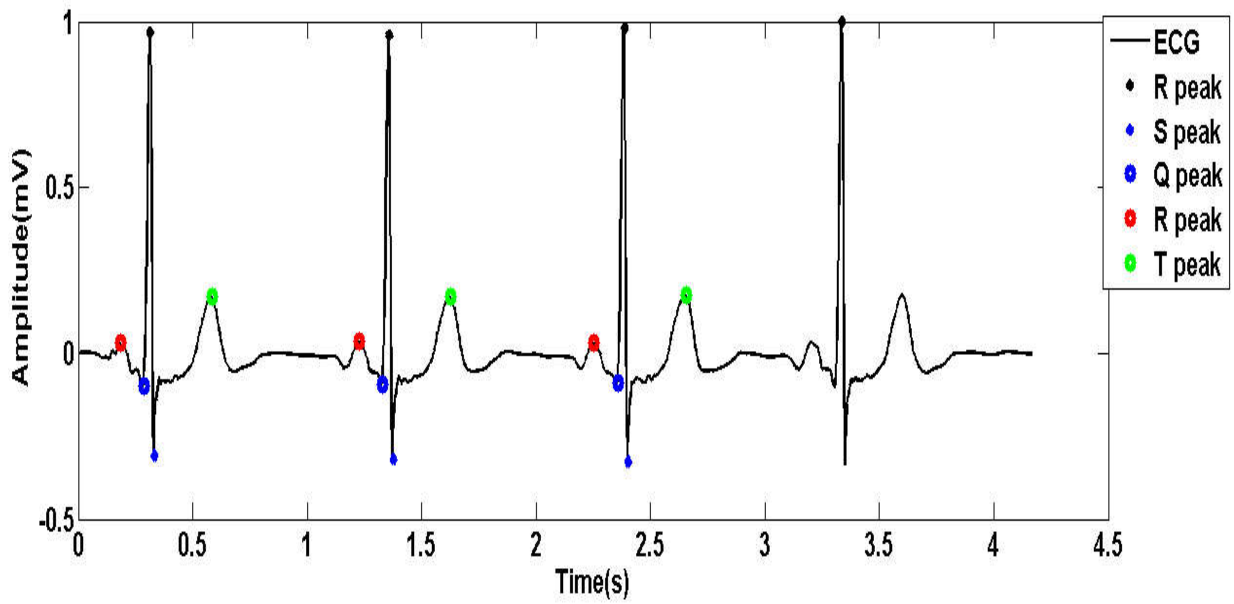
Fig. 4.2 Implementation of proposed algorithm MIT-BIH Arrhythmia database

(a) record no. 103

(b) record no. 105



(a)

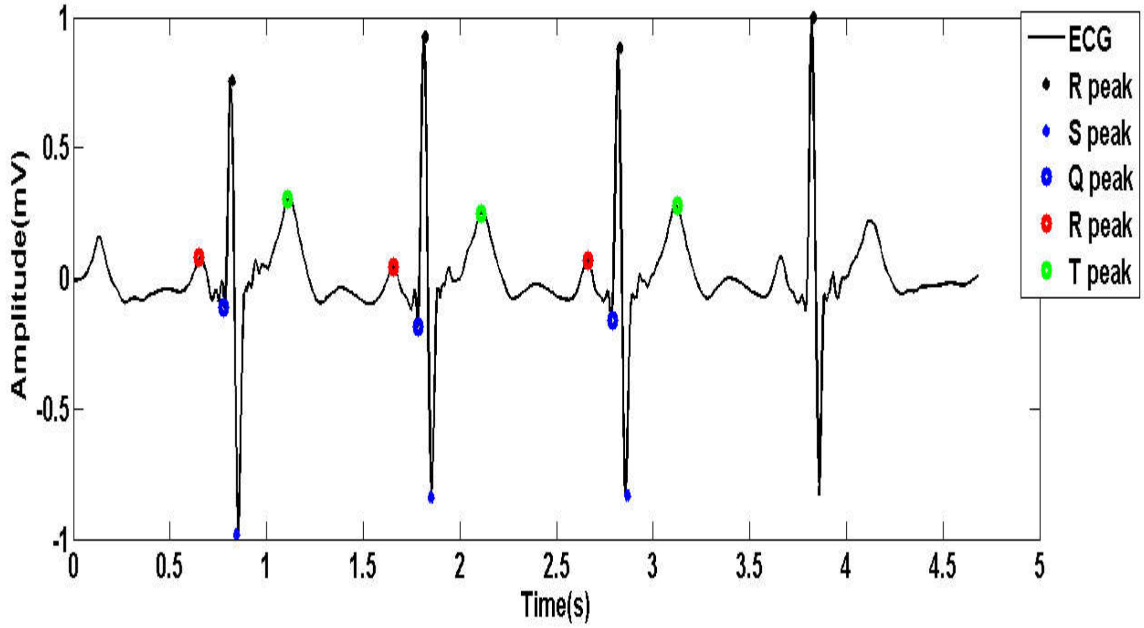


(b)

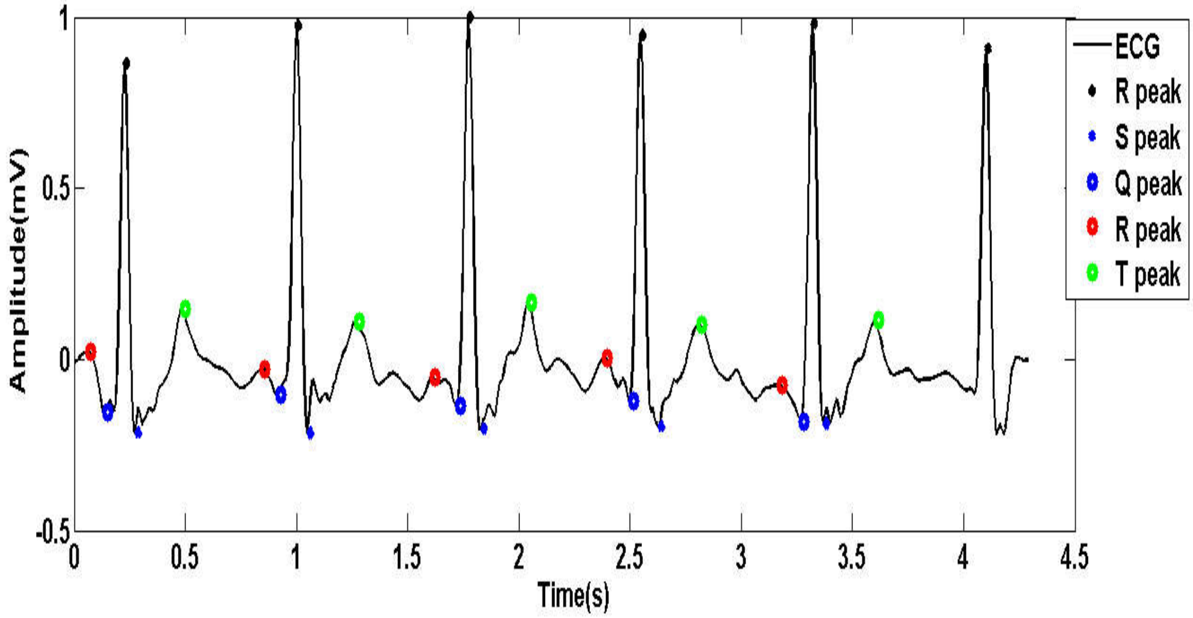
Fig 4.3 Implementation of proposed algorithm on ECG obtained from MIT-BIH ST change database

(a) record no. 300

(b) record no. 302



(a)

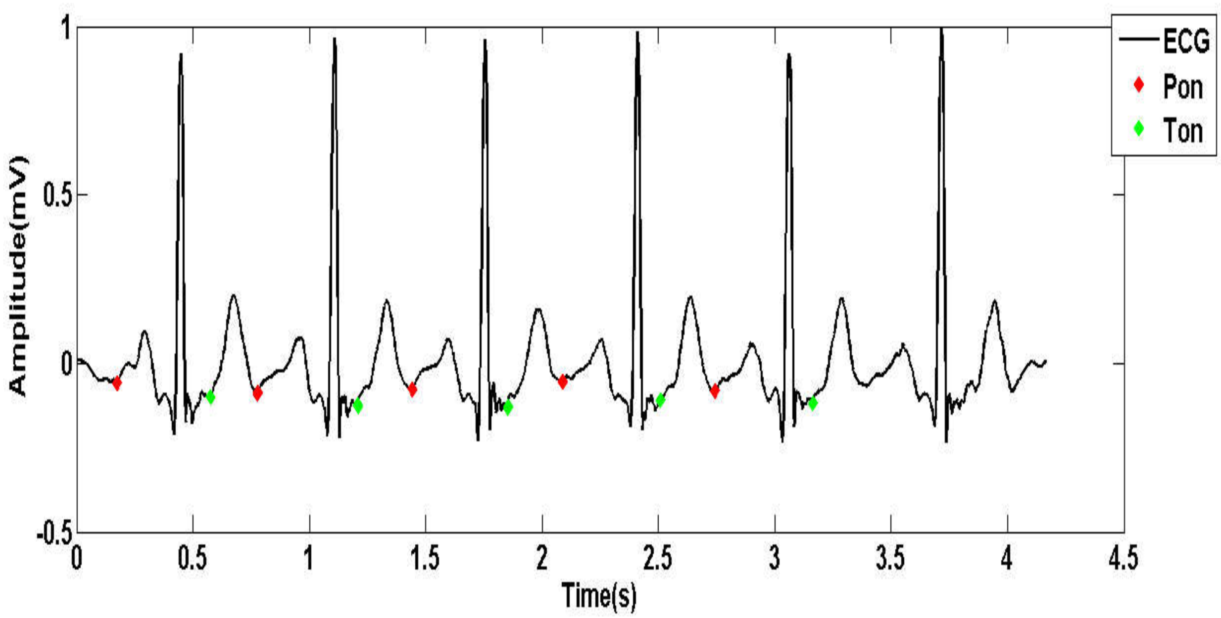


(b)

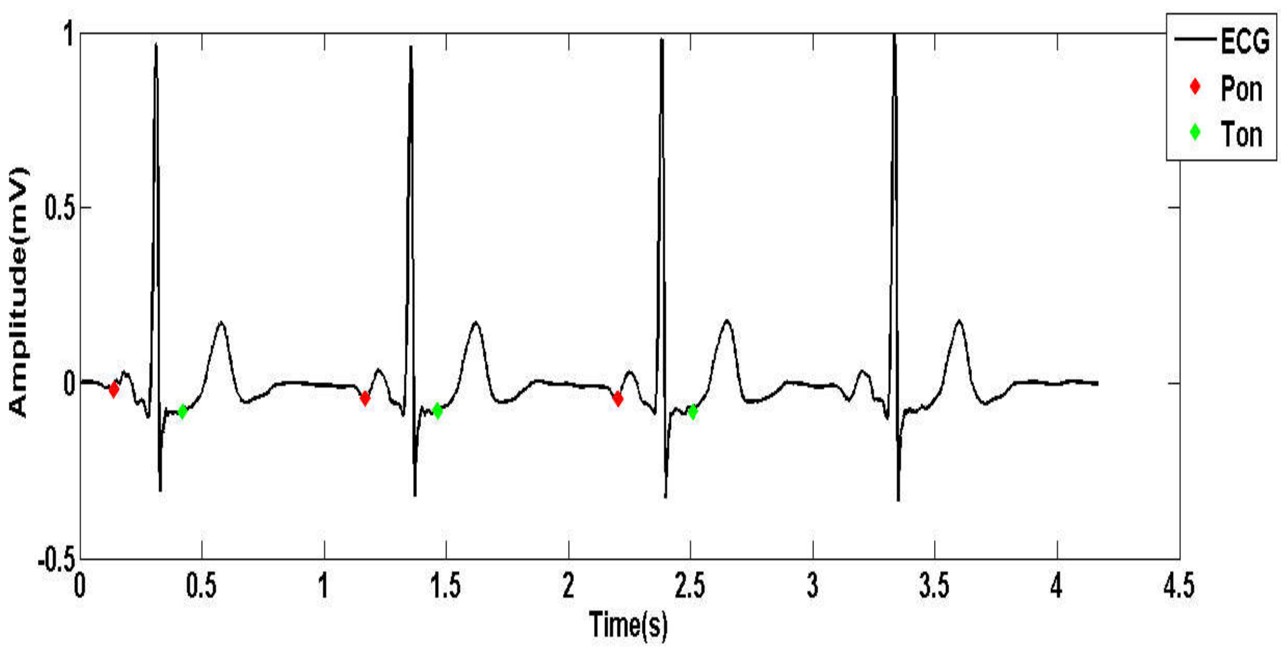
Fig. 4.4 Implementation of proposed algorithm on ECG obtained from MIT-BIH Supraventricular database

(a) record no. 802

(b) record no. 807



(a)

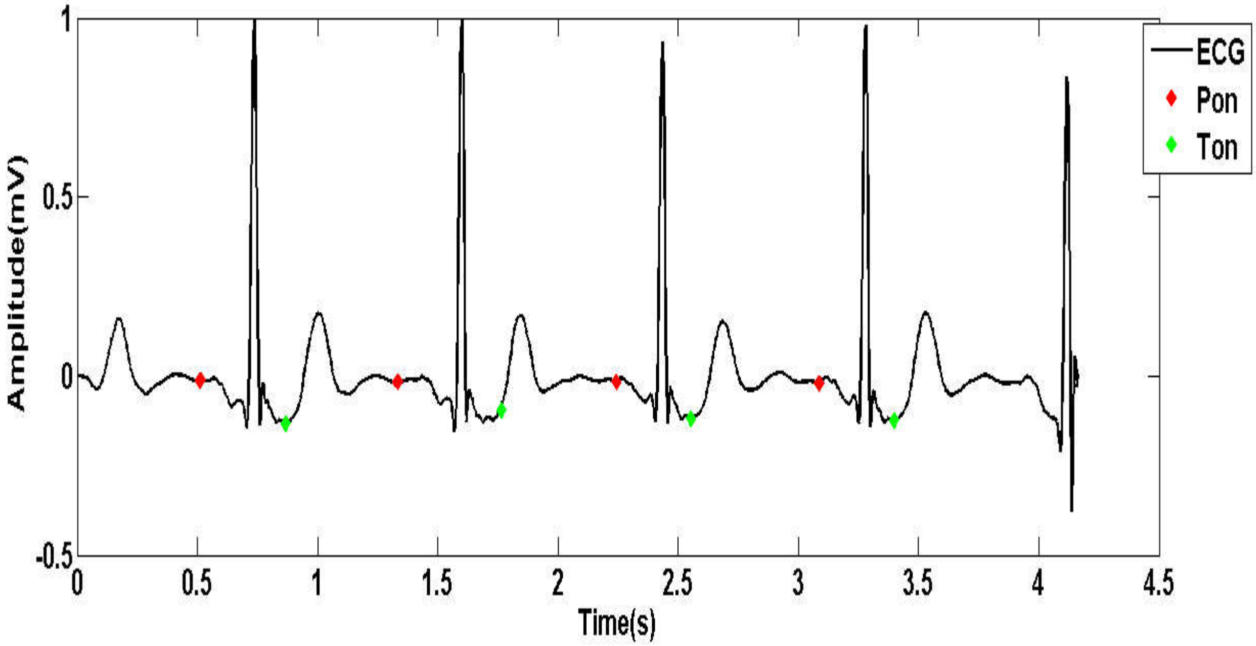


(b)

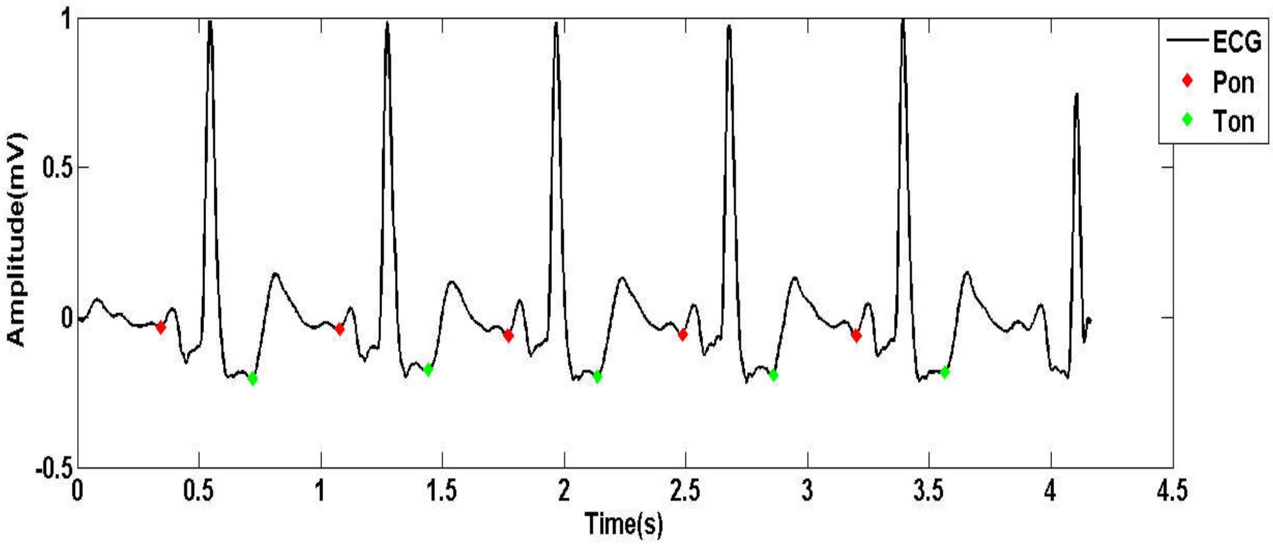
Fig. 4.5 Onset of P and T wave of ECG obtained from MIT-BIH ST change database

(a) record no. 300

(b) record no. 302



(a)



(b)

Fig. 4.6 Onset of P and T wave of ECG obtained from MIT-BIH arrhythmia

(a) record no. 103

(b) record no. 105

4.4 DISCUSSION OF SIMULATION RESULTS

To examine the performance of the proposed algorithm, three parameters are used for performance evaluation:

- **Sensitivity**: It measures the detection accuracy in the algorithm. It is measured as:

  $$S_{en} = \frac{TP}{TP+FN} \tag{4.8}$$

  In context to ECG, it is the ratio of peak (suppose R-peak) identified correctly (as R-peak). It is also called as probability of detection. Thus more is the sensitivity more accurate is the algorithm.
- **Positive predicitivity**: The more is the positive predicitivity more is rejection of false rejection.. The formula is:

  $$P_P = \frac{TP}{TP+FP} \tag{4.9}$$

  In ECG context, it is measure of positive results in true positive. Thus algorithm should give high positive predicitivity.
- **Error rate**: It is calculated as:

  $$Error\ rate = \frac{FP+FN}{Total\ detected\ beats} \tag{4.10}$$

  It is ratio of sum of false positive and false negative (in ECG, sum of no of R-peak not detected and no. of non R-peak detected as R-peak) to total detected beats or peaks. Thus error rate should be less for the proposed algorithm.

  In these above equations:

  TP is number of true positives (R peak detected as R peak)

  FN is number of false negatives (R peak not detected)

  FP is number of false positives (non- R peak detected as R peak)

The results of sensitivity, positive predicitivity and error rate of all peaks in ECG are enlisted in Table 4.3, 4.4 and 4.5 respectively.

S. No.	Record No.	P	Q	R	S	T
1	100	91	89	92	93	90
2	101	100	100	100	100	100
3	103	100	100	100	100	100
4	105	100	100	100	100	100
5	106	100	100	100	100	100
6	112	100	100	100	100	100
7	118	100	100	100	100	100
8	119	100	100	100	100	100
9	121	100	100	100	100	100
10	200	100	100	100	100	83.33
11	201	81	100	100	100	100
12	202	100	100	100	100	100
13	203	100	100	100	100	100
14	205	100	100	100	100	100
15	207	100	100	100	100	100
16	209	100	100	100	100	100
17	210	100	100	100	100	100
18	214	100	100	100	100	100
	Average	98.4	99.3	99.5	99.6	98.5

Table 4.3 Sensitivity of the proposed algorithm in detecting different peaks

S. No.	Record No.	P	Q	R	S	T
1	100	92	90	100	94	90
2	101	100	100	100	100	100
3	103	100	100	100	100	100
4	105	100	100	100	100	100
5	106	100	100	100	100	100
6	112	100	100	100	100	100
7	118	100	100	100	100	100
8	119	90	90	90	90	90
9	121	100	100	100	100	100
10	200	100	100	100	100	85
11	201	90	100	100	100	100
12	202	100	100	100	100	100
13	203	100	100	100	100	100
14	205	100	100	100	100	100
15	207	100	100	100	100	100
16	209	100	100	100	100	100
17	210	100	100	100	100	100
18	214	100	100	100	100	100
	Average	98.4	98.8	99.4	99.1	98.05

Table 4.4 Positive predictivity of the proposed algorithm in detecting different peaks

S. No.	Record No.	P	Q	R	S	T
1	100	0.11	0.12	0.09	0.07	0.11
2	101	0	0	0	0	0
3	103	0	0	0	0	0
4	105	0	0	0	0	0
5	106	0	0	0	0	0
6	112	0	0	0	0	0
7	118	0	0	0	0	0
8	119	0.1	0.1	0.1	0.1	0.1
9	121	0	0	0	0	0
10	200	0	0	0.1	0	0.30
11	201	0.01	0	0	0	0
12	202	0	0	0	0	0
13	203	0	0	0	0	0
14	205	0	0	0	0	0
15	207	0	0	0	0	0
16	209	0	0	0	0	0
17	210	0	0	0	0	0
18	214	0	0	0	0	0
	Average	0.012	0.012	**0.016**	0.0094	0.028

Table 4.5 Error rate of the proposed algorithm in detecting different peaks

Table 4.3 gives the sensitivity of the P-QRS-T peaks and P-peaks, Q-peaks, R-peaks, S-peaks and T-peaks have sensitivity of 98.4%, 98.3%, 99.5%, 99.6% and 98.5% respectively. Thus it means it has the probability of detecting R-peak as correct is 0.995. If the detected peak lie within 100ms from the annotated time, it is considered true otherwise it is false.

Table 4.4 shows the result of positive predicitivity of different waves and P-peaks, Q-peaks, R-peaks, S-peaks and T-peaks have 98.4%, 98.8%, 99.4%, 99.1% and 98.05 positive predicitivity respectively. Thus it means it has 0.006% chances of detecting other peak as R peaks which is quite less.

Table 4.5 calculates the error rate. The lesser is the error rate more accurate is our algorithm. The error rate in detecting P-peaks and Q-peaks are 0.012% whereas R-peaks, S-peaks and T-peaks are 0.016%, 0.0094% and 0.028% respectively.

R-peak error rate has drastically reduced to a small value. Thus it indicates that most of the time detected R peak is correct R-peak. The comparison of error rate among other different algorithms from literature are tabulated in Table 4.6.

J. Pan *et al.* (1985)	0.71
S. Choi *et al.* (2010)	0.54
Z. Zidelmal *et al*. (2012)	0.54
Proposed algorithm	**0.016**

Table 4.6 Comparison of error rate among different algorithms [22, 2012]

The proposed algorithm is tested over few samples of beats of length 10 seconds. In future, it will be tested on longer length of ECG.

4.5 FEATURE EXTRACTION AND SELECTION

Feature Extraction is the transforming the existing features into a lower dimensional space and feature selection is selecting the existing features without any transformation. It is the important and difficult step to choose right and appropriate features and to combine them all to form a feature set which acts as input to classifier. The features are extracted by using methods and algorithms mentioned above. If selected features are large, it causes high computational complexity whereas small number of features may not provide enough information for classification. The selection of relevant features is important. Features are extracted and combined to form a one feature set which includes following types:

- Temporal features has RR, PR, QRS and ST segment.
- Morphological features have wavelet coefficients and peak amplitude of R, P, Q, R, S and T waves.

ECG signal is decomposed to level 4 by using Daubechies as mother wavelet and the detail and approximation coefficients' maximum and minimum values for each level are used. Combining all the above 26 features for each single beat, a feature vector is made which acts as input to various classifier.

CHAPTER 5

CLASSIFICATION

Classification is the process of categorizing the data into the predefined classes. It is the backbone of the machine learning. It includes two phase: training and testing and 70% of the feature set are used in training phase and 30% are the used for testing purpose. Machine learning is bifurcated into two areas: Supervised and unsupervised learning. In supervised learning, model is trained to make correct prediction on novel data whereas unsupervised learning target output is not stated in the network, so one desires to make a useful description of the data [42].

The various machine learning algorithms and classifiers are enlisted below: support vector machine (SVM), neural network (NN), adaptive boosting (AdaBoost), random forest, decision tree. The no classifier is suitable for all types of dataset according to free lunch theorem. [9, 42]

5.1 SUPPORT VECTOR MACHINE

It separates an input $X = (x_1, x_2, \dots \dots \dots \dots . . x_n)$ of dimension n into predefined classes. In SVM, the main motive is to find the decision boundary to fully separate the dataset into classes. SVM maps the dataset of in the training phase by some kernel functions into larger dimensional feature [43]. This is written as:

$$\forall x_i : Y_i(w. x_i + \ b) \geq 1 \tag{5.1}$$

In this equation x_i is a dataset and w is learned weight vector. The above equations states that if $Y_i = +1$, then x_i belongs to class 1 otherwise to class 2. SVM has the hyper-plane when its distance between to the closest sample is large. The margin is maximized to optimize the hyper-plane. The SVM is solved as [43]

$$Maximize: \sum_{i=1}^{n} \propto_i - \frac{1}{2}\sum_{j=1}^{n} \propto_i \propto_j \ y_i y_j K(X_i X_j) \tag{5.2}$$

$$Subject\ to: 0 \leq \propto_i \leq C(i = 1, \ldots\ldots n), \sum \propto_i \propto_y = 0 \tag{5.3}$$

where $\propto \geq 0$ are Lagrange multipliers. Many $\propto_i = 0$ and the others act as support vectors. C is positive constant chosen by programmer. A large value of C can classify efficiently. If classes are categorized linearly, then the linear decision boundary is sufficient but practically decision boundary is a curve of degree greater than 1. Thus kernel function maps the input to a higher dimensions feature which can be separated linearly. A simple kernel function is defined as:

$$K(x, y) = \emptyset(x)\emptyset(y) \tag{5.4}$$

Thus, SVM is a supervised learning algorithm which receives the input in learning phase and then is used to find the new vectors or dataset by comparing them with those used in learning phase.

5.2 ARTIFICIAL NEURAL NETWORK

Nowadays, artificial neural network (ANN) is very fascinating modeling technique. There are many different ANN from simple to complicated neurons networks having linear neurons to quadratic neurons [44]. Neurons in neural network are described by transform function:

$$y = S(\sum_{i=1}^{N}(w_i x_i) - \theta) \tag{5.5}$$

in (5.5):

x_i……..inputs to neuron

w_i……weights

θ……...neural bias

$S(x)$....activation function

y……...output from neuron

Bias is reference level for input database. Weights are calculated by a back-propagation algorithm which is a learning rule involving high mathematical foundation and is standard technique for training multilayer neural networks.

Multi-layer Perceptron (MLP) is common classifier [45] whose output is:

$$y = f(w, x) \tag{5.6}$$

in the (5.6):

x…..input vector

y…..output vector

f…..function of inter-layers

w…..weights of network

MLP is arranged in layer mainly: input, hidden and output layer. The hidden layer is not directly linked to the input and output layers. Linear transform function is used in input layer and sigmoid for hidden and output layer [46]. Three layer network is shown in Fig. 5.1

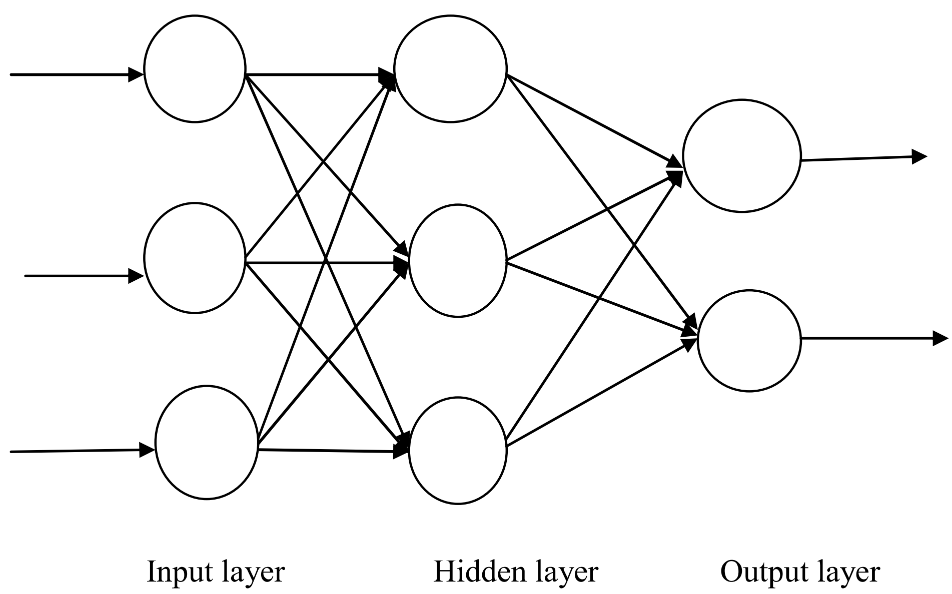


Fig. 5.1 Three layer MLP [46]

The activity of neurons in hidden layer is computed from the weights and input layer neurons. Thus it the strong tool for classification but computational complexity increases with increasing dataset.

5.3 DECISION TREE

The strategy of multi-stage classification is called decision tree. The multi-stage simple decision tree is shown in Fig 5.2.

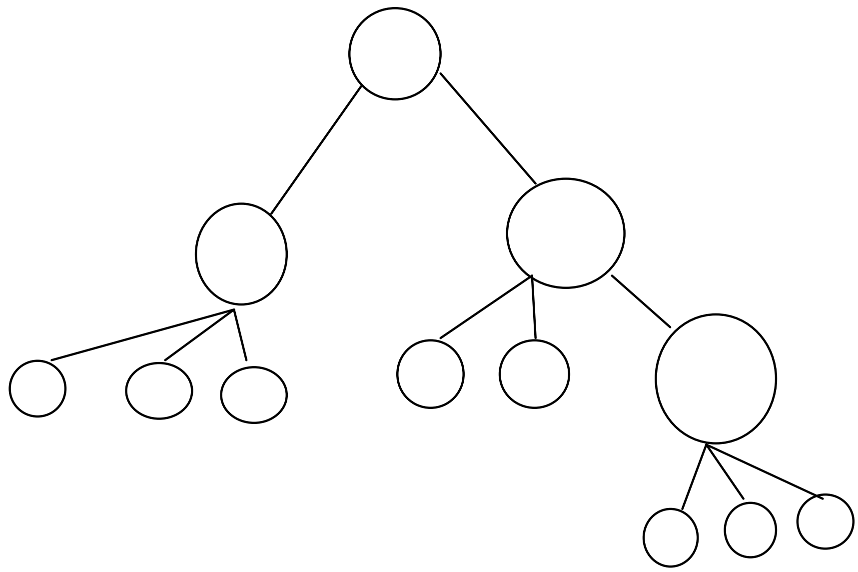


Fig 5.2 A simple decision tree [47]

To attain the best efficiency and performance, the selection of tree structure and feature subsets are of utmost importance. The appropriate decision boundaries are that in which classes are classified in number of decision step [47]. If number of features is limited, it is like calculating distance between classes. Thus, it is not good method when two or more features are used at each stage of tree.

The general decision tree algorithm is described below has gone through many evolution steps. It makes the following assumption:

- Enough reference data is present to separate the classes of interest.
- At every node Gaussian maximum likelihood rule is used.

The algorithm for decision tree is:

1. Calculate the mean vectors and covariance matrices for the classes in the training samples. Using classifier separability to make decision whether to separate the classes or to emerge or delete it from any further noticed.
2. Using the feature selection algorithm to select features in decision tree classifier. If size of subset is reduced in case of manual procedure or heuristic procedure, efficiency is improved. The class discriminating knowledge is saved for further operations in decision tree.
3. To design the decision tree either employ manual design procedure or heuristic search method
4. Draw the tree and code it for classification

In general, broad trees indicate the weightage given [47] to classifier accuracy as these trees are discriminated using many features whereas deep tree are categorized using few features reflecting weights given to efficiency which decrease the computational complexity.

5.4 RANDOM FOREST

Random forest is a collaboration of large number of decisions tree. In Random forest, tree is developed by the bootstrap of the original dataset and further at each node it selects the random set of subset of variables which are used to obtain the best split for the node. The purpose for bagging phenomenon is to obtain low variance for forest ensemble [48]. The split is evaluated by Gini impurity criteria. For a given node t and estimated class probabilities $p(k/t)$, $k = 1 \dots \dots Q$, the Gini index is:

$$G(t) = 1 - \sum_{k=1}^{Q} p^2\,(k/t) \tag{5.7}$$

where Q is number of classes. The best split is obtained when Gini index measure is zero. Thus, the splitting is repeated until Random forest consists of multiple trees.

When the Random forest is built, a new sample is classified as each class votes for the dominant or popular class. Thus classification is done according to the voting. There are advantages using this classifier:

- Error rate converges as trees number rise in forest
- No cross validation to obtain an unbiased approximation of the test set error

The error rate depends on correlation between each tree in the Random forest and their strength. The higher is the correlation, higher is the error rate whereas increase in strength of individual tree, decreases the error rate.

In Random forest, bootstrap is obtained by replacing one-third of the original data called as out-of-bag (OOB). This OOB data is used for error calculation on the non-out-of-bag data in the forest.

Thus summarizing the algorithm as follows:

- Obtain n bootstrap samples.
- Develop a tree for every bootstrap dataset. Thus choose m from M variable at every node for splitting
- A sample is predicted by majority voting for classification.
- Enumerate an OOB error rate by using non-out-of-bag sample

If m is lowered, the strength and correlation between trees is less. An optimal value for m is obtained using OOB error rate [48].

The computational complexity in Random forest:

$$O = \sqrt{M}SlogS \tag{5.8}$$

here S is the training datasets. Thus it can supervise large variables with average inspection.

5.5 ADAPTIVE BOOSTING (AdaBoost)

Boosting is a technique of turning weak classifiers into strong classifier [49, 50]. The aim is to combine many classifiers to discover classifier of the best accuracy on the training sample by ensemble the weak hypothesis. The popular algorithm for boosting is adaptive boosting (AdaBoost).The ada is strong classifier by collaborating weak learners h_i with their weight coefficients $\propto_i$ as:

$$H(x) = \sum_i \propto_i h_i(x) \tag{5.9}$$

The implementation of AdaBoost is as: First of all, weights $w_i = 1/N, i = 1, \dots \dots . N$ are initialized and main loop is started and then a Discriminant function $f_m(x) \epsilon \{-1, +1\}$ using w_i

and learning error $err_m = E_w[I_{y \neq f_{m(x)}}]$ is calculated. The weight $\propto_m = c * log\ ((1 - err_m)/err_m)$, where c constant $0 < c < 1$. The weights are updated as: $w_i = w_i.exp\left(\propto_m . I_{(y(i) \neq f_m(x))}\right)$ and this stops the main loop. The strong classifier is achieved by a linear combination of weak classifier as: $H(X) = sign[\sum_{m=1}^{M} \propto_m f_m]$. The complete algorithm is described below:

- The training set $S_c = \{(x_i, y_i), i = 1, \dots \dots . N\}$, N is feature vector set and $x_i \in X$. The class labels $y_i \in Y = \{+1, -1\}$.
- The weights $w_o = 1/N$ are initialized.
- For t $= 1, \dots \dots . . T$, do
    1. One weak hypothesis $g_i(x_i, m = 1, \dots . . M)$ for each feature set is trained, the training set is sampled by probability distribution $w_{t,i}, i = 1, \dots \dots N$.
    2. The hypothesis g_i is selected with minimum classification error ε_t .
    3. The weights are updated,

$$w_{t+1,i} = \frac{1}{Z_i} w_{t,i} e^{-\propto_i g_t(x_i) y_i} \quad (5.10)$$

$$g_i(x_i) = +1, -1 \quad (5.11)$$

Where $g_i x_i$ is classified or misclassified by weak hypothesis g_t.

$$\propto_i = 0.6 log\ (\frac{1-\varepsilon_i}{\varepsilon_i}) \quad (5.12)$$

Z_t is normalizing constant.

- Finally, the output is:

$$f_c(X) = \sum_{t=1}^{T} \propto_t g_t(X) \quad (5.13)$$

5.6 CLASSIFIERS IN ECG

As mentioned above, classification includes training and testing phase. Feature set obtained in the chapter 4 is input to different classifier to perform classification. Thus to carry down classification we used the platform of R studio version R×643.3.0 on a system having configuration i3 with an Intel CPU 2.10 GHz processor having 3 GB RAM. So the classification of ECG into healthy and unhealthy ECG is done.

Thus 70% data of from feature set is used in the training part and remaining 30% is used in testing part. All the models (SVM, NN, random forest, decision tree and AdaBoost) available in the R studio are used for the classification process. The feature set consists of 200 beats. The feature set is input to decision tree, random forest, AdaBoost, NN, SVM and their accuracy, sensitivity and positive predicitivity is calculated. The performance evaluation of the classification is done by two parameters: sensitivity and positive predicitivity (both are discussed in chapter 4).

- **Sensitivity**: In classification context, it is the number of unhealthy beats correctly identified as unhealthy beats. Thus as it is already mentioned in chapter 4, it is the probability of detection. It is called as true positive rate.
- **Positive predicitivity**: In classification context, it is the number of healthy beats identified as having same the condition.

The statistical performance metrics is shown in Fig. 5.1

	Correctly classified (positive)	Misclassified (Negative)
Normal ECG (True)	TP	TN
Abnormal ECG (False)	FT	FN

Table 5.1 Statistical performance metrics

Thus a good classifier gives maximum value for sensitivity and positive predicitivity. More is the value for both sensitivity and positive predicitivity, better will be the classifier. After input to the classifier like SVM, NN, random forest, decision tree and AdaBoost, their sensitivity and positive predicitivity are calculated. It is found that AdaBoost yields the best accuracy and sensitivity whereas all the classifier yields 100% positive predicitivity.

The accuracy, positive predicitivity and sensitivity of all the classifiers are computed and shown in tabular form in table 5.2.

CLASSIFIERS	SENSITIVITY (%)	POSITIVE PREDICITIVITY (%)	ACCURACY
Decision Tree	89	**100**	86.20
Adaptive boosting	**96**	**100**	**96.55**
Random Forest	93	**100**	93.1
SVM	93	**100**	93.1
Neural Network	83	**100**	82.75

Table 5.2 Performance evaluation of classifiers

The 100% positive predicitivity means all healthy beats are correctly identified as healthy beats. No healthy person has reports of unhealthy beat.

Thus the collaboration of the proposed system and the classifier has resulted in the 100% positive predicitivity for all the models of classifiers used but varying sensitivity and accuracy from classifier to classifier.

CHAPTER 6

CONCLUSIONS AND FUTURE SCOPE OF WORK

PRECISELY SPEAKING, wavelet transform is the most heated topic and purely based on mathematics and coding. Only in a few years of its existence, it has displayed great potential and suitability in various different fields. Therefore we tried to provide an overview of wavelet transform highlighting basic idea as its detail mathematics and proofs are beyond the scope of this thesis. The major objectives: removal of baseline wandering and ECG denoising are achieved using discrete wavelet transform.

The selection of an appropriate mother wavelet and its scale for given signal is discussed in ECG denoising chapter. After ECG denoising, employing soft thresholding technique and Donoho threshold value, a clean ECG signal is obtained

Further, our aim was to develop an algorithm to identify fiducial points, various intervals of ECG wave which helps to identify ECG beat into healthy or unhealthy. Combining temporal and morphological features, a feature set is formed which is input to classifiers like NN, random forest, SVM, AdaBoost and decision tree. The algorithm has given a very less error rate of 0.016% in detecting R-peak in ECG waveform.

Among classifiers adaptive boosting gave the maximum accuracy of 96.55% and sensitivity of 96% whereas the proposed algorithm proved effective in estimating positive predicitivity (100%) for all the classifier.

The wavelet transform is a promising tool in non-invasive ECG thus providing an efficient method for ECG processing. The optimal time-frequency resolution is the major highlight of the wavelet transform. Since the application of wavelet transform in ECG is comparatively new area of research, further investigation of many methodological aspects will improve its clinical usefulness. The collaboration of more efficient classifiers will improve the accuracy.

FUTURE SCOPE OF THE WORK

There is always enough room for further improvement and innovation.

- We only handled white noise, other artifacts like color noise implemented by an autoregressive models should be considered in the future work.
- The collaboration of more efficient classifiers will improve the accuracy.

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