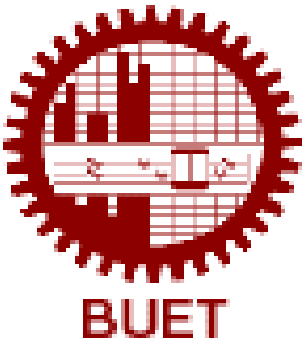
DETECTION OF CARDIAC ABNORMALITY USING DISCRETE WAVELET COEFFICIENTS OF ECG

by

Md. Kamruzzaman

A Project Report Submitted to the
Department of Electrical and Electronic Engineering, BUET,
in partial fulfilment of the requirements for the degree of

Master of Engineering in
Electrical and Electronic Engineering



DEPARTMENT OF ELECTRICAL AND ELECTRONIC ENGINEERING
BANGLADESH UNIVERSITY OF ENGINEERING AND TECHNOLOGY

June 2010

The project titled **Detection of Cardiac Abnormality Using Discrete Wavelet Coefficients of ECG** Submitted by **Md. Kamruzzaman,** Roll No: **040406261 P**, Session **April 2004** has been accepted as satisfactory in partial fulfilment of the requirements for the degree of **Master of Engineering in Electrical and Electronic Engineering** on **30 June 2010**.

BOARD OF EXAMINERS

1.	_____ Dr. Md. Aynal Haque Professor Dept. of EEE, BUET, Dhaka	Chairman
2.	_____ Dr. Mohammed Imamul Hassan Bhuiyan Associate Professor Dept. of EEE, BUET, Dhaka	Member
3.	_____ Dr. Mohammad Ariful Haque Assistant Professor Dept. of EEE, BUET, Dhaka	Member

DECLARATION

It is hereby declared that the work presented here in this project or any part it has not been or being submitted elsewhere for the award of any degree or diploma.

_____

Md. Kamruzzaman

ACKNOWLEDGEMENTS

I would like to express my gratitude to my erudite supervisor Dr. Md. Aynal Haque, Professor Department of Electrical and Electronic Engineering, BUET for his kind supervision to initiate the idea of this paper. His continuous assistance inexorable enthusiasm encouragement, valuable suggestions were outstanding which made this task a reality. His innovative idea, modern outlook inspired the authors to perform this task. It is noteworthy as well as ineffable that his generosity and helping attitude was the key to make the job a wholesome one.

I wish to express my thanks and regards to the Head of the Department of Electrical and Electronic Engineering, BUET, for his support and cooperation.

Sincere thanks to my parents, wife, colleagues, friends and well wishers for their encouragement, advice and support to complete my project.

Table of Contents

ABSTRACT

The electrocardiogram (ECG) is the record of variation of bioelectric potential of human heart beats with respect to time. ECG represents the electrical activity of heart and is a well-established tool for the diagnosis of cardiac condition. In order to obtain accurate information about cardiac condition of a person, correct interpretation of ECG is essential. The objective of this work is to devise an automatic computer based detection technique for five particular types of cardiac abnormalities by processing ECG signal with better accuracy and less computational time.

Five particular types of cardiac phenomena that have been considered are: normal beat, left bundle branch block (LBBB), right bundle branch block (RBBB), premature ventricular contraction (PVC) and atrial premature beat (APB). A total set of 19 records have been taken from MIT- BIH arrhythmia database as test data. For all the test records, discrete wavelet transform (DWT) with 40,000 samples up to a decomposition level of 4 is performed in the Matlab 7.4.0 environment. Five different types of mother wavelet functions are used for this analysis. These are: haar, coiflet2, symlet4, daubechies10 and biorthogonal6.8. The maximum value of the approximation coefficients of level 4 is selected as the indicating parameter, which is used to distinguish between different abnormalities.

A comparison is made among the performances of different types of mother wavelets to select the best one to differentiate cardiac abnormalities. Among the five wavelets that we have used in our study, daubechies10 (db10), the only one possessing asymmetric property, has provided the most optimum result. So as an outcome of this analysis we can conclude that asymmetric mother wavelet functions are more effective than the symmetric ones for distinguishing different types of ECG beats. Further analysis with more number of symmetric and asymmetric wavelet functions should be carried out to generalize the findings of this study and to detect other types of cardiac abnormalities.

LIST OF FIGURES

LIST OF TABLES

Chapter 1
INTRODUCTION

1.1 ECG Signal Processing

Heart is one of the most vital organs of human body. Electrocardiogram (ECG) represents the electrical activity of heart and it is the primary tool for detection of heart diseases. So study of ECG signal is one of the major topics in biomedical engineering, to be more specific, in biomedical signal processing.

In ECG examination of the various waves and their characteristics, yields important diagnostic information. The ECG has become so familiar to the general population that it is part of the logo of many medical organizations, representing the technical side of medicine. Being an electrical representation, it signifies vitality and urgency. In various television medical dramas, an isoelectric ECG (no cardiac electrical activity, also known as flat line) is often used as a symbol of death or at least extreme medical peril.

The ECG machine has a rich history that has lead to its prominent future in medical equipment and supplies. In 1856 Kollicker and Mueller discovered the electrical activity of the heart when a frog sciatic nerve/gastrocenemius preparation fell onto an isolated frog heart and both muscles contracted synchronously.[22] Alexander Muirhead attached wires to a feverish patient's wrist to obtain a record of the patient's heartbeat while studying for his DSc (in electricity) in 1872 at St Bartholomew's Hospital. This activity was directly recorded and visualized using a Lippmann capillary electrometer by the British physiologist John Burdon Sanderson.

The first to systematically approach the heart from an electrical point-of-view was Augustus Waller, working in St Mary's Hospital in Paddington, London. His electrocardiograph machine consisted of a Lippmann capillary electrometer fixed to a projector. The trace from the heartbeat was projected onto a photographic plate which was itself fixed to a toy train. This allowed a heartbeat to be recorded in real time. In 1911 he still saw a little clinical application for his work.

A breakthrough came when Willem Einthoven, working in Leiden, The Netherlands, used the string galvanometer invented by him in 1901. This was much more sensitive than the capillary electrometer that Waller used. Einthoven assigned the letters P, Q, R, S and T to the various deflections, and described the electrocardiographic features of a number of cardiovascular disorders. In 1924, he was awarded the Nobel Prize for his outstanding work.

In 1924 , Woldemar Mobitz publishes his classification of heart blocks (Mobitz type I and type II) based on the electrocardiogram and jugular venous pulse waveform findings in patients with second degree heart block. In 1928, Ernstine and Levine reported the use of vacuum-tubes to amplify the electrocardiogram instead of the mechanical amplification of the string galvanometer. At the same year, Frank Sanborn's company converted their table model electrocardiogram machine into their first portable version weighing 50 pounds and powered by a 6-volt automobile battery.

In 1932 Charles Wolferth and Francis Wood describe the clinical use of chest leads. A major breakthrough came in 1934. By joining the wires from the right arm, left arm and left foot with 5000 Ohm resistors Frank Wilson defines an 'indifferent electrode' later called the 'Wilson Central Terminal'. The combined lead acts as an earth and is attached to the negative terminal of the ECG. An electrode attached to the positive terminal then becomes 'unipolar' and can be placed anywhere on the body. Wilson defines the unipolar limb leads VR, VL and VF where 'V' stands for voltage.

In 1942 Emanuel Goldberger increases the voltage of Wilson's unipolar leads by 50% and creates the augmented limb leads aVR, aVL and aVF. When added to Einthoven's three limb leads and the six chest leads we arrive at the 12-lead electrocardiogram that is used today.

Further progresses were made in detection of cardiac abnormalities based on the observation of ECG waveshapes. In 1944 Young and Koenig report deviation of the P-R segment in a series of patients with atrial infarction. In 1947 Gouaux and Ashman describe an observation that helps differentiate aberrant conduction from ventricular tachycardia. In 1963 Baule and McFee are the first to detect the magnetocardiogram which is the electromagnetic field produced by the electrical activity of the heart. It is a method that

can detect the ECG without the use of skin electrodes. Although potentially a useful technique it has never gained clinical acceptance, partly because of its greater expense. [22] In 1968, Journal of Electrocardiography, the Official Journal of the International Society for Computerized Electrocardiology and the International Society of Electrocardiology, was founded by Zao and Lepeschkin. In 1968 Henry Marriott introduces the Modified Chest Lead 1 (MCL1) for monitoring patients in Coronary Care.

In 1993 Robert Zalenski, a Professor of Wayne State University Detroit and his colleagues published an influential article on the clinical use of the 15-lead ECG which routinely uses V4R, V8 and V9 in the diagnosis of acute coronary syndromes. Like the addition of the 6 standardised unipolar chest leads, these additional leads increase the sensitivity of the electrocardiogram in detecting myocardial infarction.

The latest technology in this field is wireless ECG. In 1999 Researchers from Texas show that 12-lead ECGs transmitted via wireless technology to hand-held computers is feasible and can be interpreted reliably by cardiologists.[17] In 2005 Danish cardiologists reported the successful reduction in the time between onset of chest pain and primary angioplasty when the ECG of patients is transmitted wirelessly from ambulance to the cardiologist's handheld PDA (Personal Digital Assistant). The clinician can make an immediate decision to redirect patients to the catheter lab saving time in transfers between hospital departments.

1.2 Historical Background

Biomedical engineering achievements range from early devices, such as crutches, platform shoes, wooden teeth, and the ever-changing cache of instruments in a doctor’s black bag, to more modern marvels, including pacemakers, ECG machine, the heart-lung machine, dialysis machines, diagnostic equipment, imaging technologies of every kind, and artificial organs, implants and advanced prosthetics. In its broadest sense, biomedical engineering has been with us for centuries, perhaps even thousands of years. In 2000, German archeologists uncovered a 3,000-year-old mummy from Thebes with a wooden prosthetic tied to its foot to serve as a big toe. Researchers said the wear on the bottom surface suggests that it could be the oldest known limb prosthesis. Egyptians also used hollow reeds to look and listen to the internal goings on of the human anatomy. No matter what

the date, biomedical engineering has provided advances in medical technology to improve human health. As an academic endeavor, the roots of biomedical engineering reach back to early developments in electrophysiology, which originated about 200 years ago.

An early landmark in electrophysiology occurred in the 19th century. Hermann von Helmholtz is credited with applying engineering principles to a problem in physiology and identifying the resistance of muscle and nervous tissues to direct current. In 1895, Wilhelm Roentgen discovered X-ray which was a major invention on this field.

Biomedical engineering's unique mix of engineering, medicine and science emerged alongside biophysics and medical physics early this century. At the outset, the three were virtually indistinguishable and none had formal training programs. Between World War I and World War II a number of laboratories undertook research in biophysics and biomedical engineering. The Oswalt Institute for Physics in Medicine, established in 1921 in Frankfurt, Germany, started to offer formal training on this topic .The Institute's founder, Friedrich Dessauer, pioneered in research into the biological effects of ionizing radiation.

Progress was rather slow until World War II, but after that a surplus of electronic equipment, such as amplifiers and recorders became available which stimulated the progress. At that time many technicians and engineers, both within industry and on their own, started to experiment with and modify existing equipments for medical use. This process occurred primarily during the 1950s and the results were often disappointing, for the experimenters soon learned that physiological parameters are not measured in the same way as physical parameters. This limitation led to the further analysis and research in order to obtain advanced data acquisition, processing and techniques in the field of biomedical engineering.

Following the Second World War, administrative committees began forming around the combined areas of engineering, medicine and biology. A biophysical society was formed in Germany in 1943. Five years later, the first conference of engineering in medicine and biology convened in the United States, under the auspices of the Institute of Radio Engineers, the American Institute for Electrical Engineering, and the Instrument Society of

America. In the following years several conventions and meetings on this subject took place.

The diversity of work in biomedical engineering and the diversity of background of the people contributing to this field made it difficult for a single organization to represent everyone. The International Federation for Medical and Biological Engineering (IFMBE) was founded in 1958. In the late 1960s the Alliance for Engineering in Medicine and Biology was formed and in 1968, the Biomedical Engineering Society was formed. Besides this the Whitaker Foundation , created in 1975 upon the death of engineer and philanthropist U. A. Whitaker, supported interdisciplinary medical research and education with the principal focus being on biomedical engineering. It eventually became the largest private benefactor of biomedical engineering in USA. The American Institute for Medical and Biological Engineering (AIMBE) was created in 1991, as an umbrella organization to address the issues of public policy and public and professional education that comprise these engineering sciences.

Gradually biomedical engineering programs, departments and institutes were established in different parts of the world. The field is thus expanding rapidly and is going to put further impact on human life in days to come.

The electrocardiogram (ECG) is the record of variation of bioelectric potential with respect to time as the human heart beats. ECG signals, considered as representative signals of cardiac physiology, are strong tools in diagnosing cardiac disorder. It provides valuable information about the functional aspects of the heart and cardiovascular system. ECG consists of P wave, QRS complex and T wave. The state of cardiac health is generally reflected in the shape of ECG waveform and heart rate. However, as the biosignals are nonstationary signals, this reflection may occur at random in the time scale. In this situation, the disease symptoms may not show up all the time, but would manifest at certain irregular intervals during the day. Therefore, for effective diagnostics, detail study of ECG pattern and heart rate variability signal is necessary [1]. In many cases the collection of data is carried out for over several hours. Thus, the volume of the data becomes enormous, and the study is tedious and time consuming. Naturally, the possibility of the analyst missing (or misreading) vital information is high. In such scenario computer-based analysis and classification of diseases can be very helpful in diagnostics.

But ECG pattern recognition may become a difficult problem even with the aid of a computer as ECGs differ significantly even for the same type and for the same patient [2]. Most of the time the desired ECG signals are either corrupted or embedded in noise. To overcome these problems appropriate signal processing techniques, like wavelet analysis can be employed for ECG signals.

The wavelet transform (WT) has emerged over recent years as a key time–frequency analysis and coding tool for the ECG [3]-[4]. WT allows a signal to be decomposed such that frequency characteristics and the location of particular features in a time series may be highlighted simultaneously [5]-[9]. The ECG signals are decomposed into time-frequency representations using discrete wavelet transform (DWT). The major advantage of the DWT is its great time and frequency localization ability, which enables it to reveal the local characteristics of the input signal. Discrete wavelet techniques have been used for ECG peak detection, detection of ECG characteristic points, heart rate variability analysis, etc [10] – [16]. A direct and simplified method to detect cardiac abnormalities based on the numerical values of discrete wavelet coefficients is a bit novel approach, which this study has aimed at. The standard ECG from different sources [17] – [19] has been used by many researchers for unified comparison with WT based mathematical tools [20].

1.3 Motivation

Electrocardiography or ECG is a primary tool for the diagnostic of cardiac diseases. This diagnosis is usually performed by visual inspection and understanding. Depending on the cardiac condition of the subject, the ECG wave shape takes different forms. By examining these wave shapes and their characteristics, a physician detects the cardiac condition of the patient.

The main objective of this thesis is to develop an automatic detection method of some particular cardiac abnormalities by ECG signal processing. The implementation of this technique will eliminate the need of visual inspection. By applying appropriate signal processing techniques to the raw ECG signal, certain parameters will be extracted and based on the values of these parameters; the system will automatically decide the cardiac phenomenon which is prevalent in the subject.

Five particular types of cardiac phenomena have been considered in this study. These are: normal heart beat, left bundle branch Block (LBBB), right bundle branch block (RBBB), atrial premature beat (APB) and premature ventricular contraction (PVC). For each of these phenomena, some particular ECG signals have been selected as samples from the MIT-BIH Arrhythmia Database, an online source of ECG records, used worldwide for ECG related studies.

As an effective signal processing tool that can be used on these signals, we have chosen is discrete wavelet transform (DWT). DWT analysis of sample signals is performed using five different types of mother wavelets- haar, db10, coif2, bior6.8 & sym4.
So the main objectives of this thesis are:

- Analysis of the results and choosing an optimum method of analysis.
- Comparing the performance of different mother wavelets and choosing one that can provide the best performance.
- Developing an algorithm for differentiating the cardiac phenomenon in consideration and analyzing its effectiveness.

1.4 Organization of the Dissertation

The rest of the report is organized as the following:
Chapter 2, Deals with the formal description of physiologic waveform and background theory on ECG signal and an overview of various cardiac phenomena used in our study.
Chapter 3, Provides a brief description on discrete wavelet transform and the mother wavelet functions that we have used in our analysis.
Chapter 4, Describes the detailed methodology of this study i.e how ECG signal classification is done using Wavelet Transform.
Chapter 5, Results and Simulations, describes the comparative study of the result and simulations of different techniques used for the ECG beat classification.
Chapter 6, Contains a brief overview regarding the achievements, limitations and future scope of this study.

Chapter 2

WAVELET TRANSFORM

2.1 Introduction

Wavelets are a powerful tool for the representation and analysis of such physiologic waveforms because a wavelet has finite duration (compact support) as contrasted with Fourier methods based on sinusoids of infinite duration. The Fourier transform is a tool widely used for many scientific purposes, but it is well suited only to the study of stationary signals where all frequencies have an infinite coherence time. The Fourier analysis brings only global information which is not sufficient to detect compact patterns. Gabor introduced a local Fourier analysis, taking into account a sliding window, leading to a time frequency-analysis. This method is only applicable to situations where the coherence time is independent of the frequency. This is the case for instance for singing signals which have their coherence time determined by the geometry of the oral cavity. Morlet introduced the Wavelet Transform in order to have a coherence time proportional to the period. The wavelet transform or wavelet analysis is probably the most recent solution to overcome the shortcomings of the Fourier transform. In wavelet analysis the use of a fully scalable modulated window solves the signal-cutting problem. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In the end the result will be a collection of time- frequency representations of the signal, all with different resolutions. Because of this collection of representations we can speak of a multi-resolution analysis. In the case of wavelets we normally do not speak about time-frequency representations but about time-scale representations, scale being in a way the opposite of frequency, because the term frequency is reserved for the Fourier transform.

2.2 Wavelet Characteristics

Any function cannot be considered as a wavelet. A function should have the following properties to be a wavelet:

2.2.1 Admissibility Condition

The admissibility condition implies that the Fourier Transform of $\Psi(t)$ vanishes at the zero frequency, i.e.

$|\Psi(\omega)|2=0$, at $\omega=0$

$\Psi(\omega)$ is the Fourier Transform of $\Psi(t)$

This means that wavelets must have a bandpass like spectrum.

A zero at the zero frequency also means that the average value of the wavelet in the time domain must be zero, i.e.

$$\int \Psi(t)dt = 0$$

And therefore it must be oscillatory. In other words, $\Psi(t)$ must be a wave.

2.2.2 Regularity Condition

Regularity condition states that the wavelet function should have some smoothness and concentration in both time and frequency domain.

Using Taylor series on original wavelet transform:

$$\gamma(s,\tau) = \frac{1}{\sqrt{s}}\int x(t)\,\Psi^{*}{}_{s,\tau}(t)dt$$

We get

$$\gamma(s,0) = \frac{1}{\sqrt{s}}\left[\sum_{p=0}^{n} x^{p}(0)\int \frac{t^{p}}{p!}\Psi\left(\frac{t}{s}\right)dt + O(n+1)\right]$$

Here, x^{p} stands for pth derivative of x(t) and $O(n+1)$ is the remaining parts of the series.

Now, moments, $M_p = \int t^{p}\Psi(t)dt$

So,

$$\gamma(s,0) = \frac{1}{\sqrt{s}}\left[x(0)M_0 s + \frac{x^{(1)}(0)}{1!}M_1 s^{2} + \frac{x^{(1)}(0)}{1!}M_2 s^{3} + \cdots + + \frac{x^{(1)}(0)}{1!}M_n s^{n+1} + O(s^{n+2})\right]$$

From admissibility condition, 0th moment, $M_0 = 0$. So, the first of the right side is zero.

2.3 Wavelet Transformation Types

There are various types of wavelet transforms are available. Such as: continuous wavelet transforms (CWT), discrete wavelets transform (DWT), discrete time wavelets transform

(DTWT) etc. In our study we used DWT to classify the ECG beats. Some basic wavelet transform are described below:

2.3.1 Continuous Wavelet Transforms

If the input signal is continuous and time-scale parameters are continuous, then the transform is called continuous wavelet transform. A continuous wavelet transform (CWT) analyzes continuous time functions using a base function, which is the mother wavelet. The signal is then represented by a series of wavelet functions which are scaled and translated functions derived from the mother wavelet. CWT requires more computation than discrete wavelet transform and it can only be used to model continuous signals. CWT does give both time and frequency information.

Let us consider a mother wavelet function $\psi(t)$ of zero average:

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0$$

When this function is dilated by a factor of a and translated by another scalar b, we get another wavelet denoted by $\psi^{a,b}(t)$ and given by

$$\psi^{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)$$

The continuous wavelet transform $X_w(a, b)$ of a function $x(t)$ at a scale *"a"* and position *"b"* is computed by correlating $x(t)$ with the wavelet $\psi^{a,b}(t)$

$$X_w(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} \overline{\psi}\left(\frac{t-b}{a}\right)x(t)dt$$

Where $\overline{\psi}^{a,b}(t)$ is the algebraic dual of the mother wavelet $\psi^{a,b}(t)$.

2.3.2 Discrete Wavelets Transforms

The continuous wavelets have an infinite number of wavelets in the wavelet transform which is not practical. It is necessary to reduce the wavelet numbers to a more manageable count. To overcome this problem discrete wavelets have been introduced. Discrete wavelets are continuously scalable and translatable but can only be scaled and translated in discrete steps. This is achieved by modifying wavelet as:

$$\Psi_{j,k}(t) = \frac{1}{\sqrt{s^j}}\Psi\left(\frac{t - k\tau s^j}{s^j}\right)$$

Where, s = Scale parameter defined as 1/frequency

τ = Translation, related to time

j and k are integers.

We usually choose s=2, so that the sampling of the frequency axis corresponds to dyadic sampling.

Discrete wavelet transform can be got from the sampling of continuous wavelet transform (CWT). In this sampling purpose, we use the filters defined as:

$$h_k(t) = a^{-\frac{k}{2}}h(a^{-k}t), \quad a > 1, k = integer$$

In frequency domain,

$$H_k(j\Omega) = a^{\frac{k}{2}}H(ja^k\Omega)$$

And discrete wavelet transform (DWT) can be obtained as:

$$X_{DWT}(k,n) = a^{-\frac{k}{2}}e^{-j\Omega_0 T}\int_{-\infty}^{\infty} x(t)h\left(a^k(\tau - t)\right)dt$$

Now,

$$h\left(a^{-k}(na^kT - t)\right) = h(nT - a^kt)$$

which gives,

$$X_{DWT}(k,n) = a^{-\frac{k}{2}}\int_{-\infty}^{\infty} x(t)h(nT - a^{-k}t)dt$$

$$or, \; X_{DWT}(k,n) = \int_{-\infty}^{\infty} x(t)h_k(na^kT \quad t)dt$$

2.3.3 Wavelet Decomposition

Using a smaller number of features to represent the ECG signals is particularly important for recognition and diagnostic purposes. Wavelet transforms allow a signal to be decomposed such that frequency characteristics and the location of particular features in a time series may be highlighted simultaneously. The ECG signals are decomposed into time-frequency representations using Discrete Wavelet Transform (DWT). The major

advantage of the DWT is its great time and frequency localization ability, which enables it to reveal the local characteristics of the input signal.

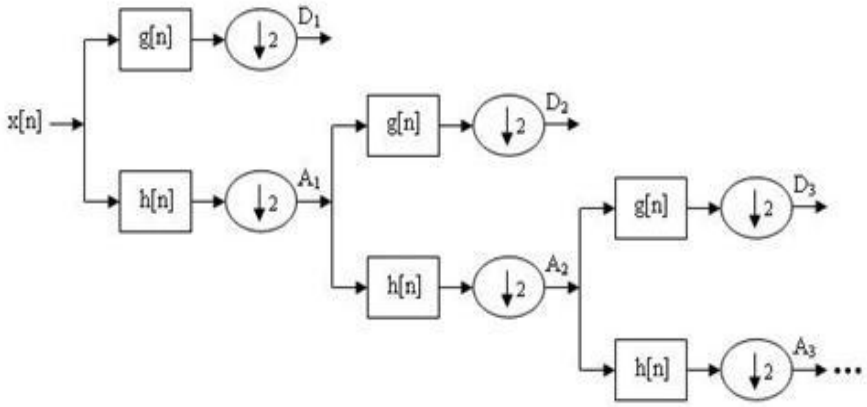


Figure 2.1: Basic schematic of wavelet decomposition

All wavelet transforms can be specified in terms of a low-pass filter h, which satisfies the standard quadrature mirror filter condition:

$$H(z)\,H(z^{-1}) + H(-z)\,H(-z^{-1}) = 1$$

where H (z) denotes the z-transform of the filter h. Its complementary high-pass filter can be defined as

$$G(z) = z\,H(-z^{-1})$$

A sequence of the filters with increasing length (indexed by i) can be obtained.

$$H_{i+1}(z) = H(z^{2i})\,H_i(z)$$

$$G_{i+1}(z) = G(z^{2i})\,H_i(z),\ i = 0,1,\ldots\ldots I-1$$

with initial condition H0 (z) = 1. It is expressed as a two-scale relation in time domain

$$h_{i+1}(k) = [2h]\uparrow 2i * h_i(k)$$

$$g_{i+1}(k) = [2g]\uparrow 2i * h_i(k)$$

where the subscript [2.]↑m indicates the up sampling by a factor of m and k is the equally sampled discrete time.

The normalized wavelet and scale basis function $\Phi_{i,l}(k)$, $\psi_{i,l}(k)$ can be defined as

$$\Phi_{i,l}(k) = 2^{i/2}\,h_i(k - 2^i l) \quad \text{and} \quad \psi_{i,l}(k) = 2^{i/2}\,g_i(k - 2^i l)$$

where the factor $2^{i/2}$ is an inner product normalization, i and l are the scale parameter and the translation parameter, respectively. The discrete wavelet transform (DWT) decomposition can be described as

$$a_{(i)}(l) = x(k) * \Phi_{i,l}(k)$$

$$d_{(i)}(l) = x(k) * \psi_{i,l}(k)$$

where a(i) (l) and d(i) (l) are the approximation coefficients and the detail coefficients at resolution i, respectively.

2.4 Properties of Mother Wavelets

We distinguish five types of wavelets:

1. Orthogonal wavelets with FIR filters: These wavelets can be defined through the scaling filter. Predefined families of such wavelets include Haar, Daubechies, Coiflets, and Symlets.
2. Biorthogonal wavelets with FIR filters: These wavelets can be defined through the two scaling filters wr and wd, for reconstruction and decomposition respectively. The BiorSplines wavelet family is a predefined family of this type.
3. Orthogonal wavelets without FIR filter, but with scale function: These wavelets can be defined through the definition of the wavelet function and the scaling function. The Meyer wavelet family is a predefined family of this type.
4. Wavelets without FIR filter and without scale function: These wavelets can be defined through the definition of the wavelet function. Predefined families of such wavelets include Complex Gaussian and Shannon.
5. Complex wavelets without FIR filter and without scale function: These wavelets can be defined through the definition of the wavelet function. Predefined families of such wavelets include Complex Gaussian and Shannon.

There qualities of these wavelet families vary according to several criteria. Some of the criteria are:

- The support of Ψ, Φ (and Φ, Φ): the speed of convergence to 0 of these functions ($\Psi(t)$ or $\Phi(\omega)$) when the time t or the frequency ω goes to infinity, which quantifies both time and frequency localizations
- The symmetry, which is useful in avoiding de-phasing in image processing
- The number of vanishing moments for Ψ or for Φ (if it exists), which is useful for compression purposes
- The regularity, which is useful for getting nice features, like smoothness of the reconstructed signal or image, and for the estimated function in nonlinear regression analysis

These are two properties that allow fast algorithm and space-saving coding:

- The existence of a scaling function Φ
- The orthogonality or the biorthogonality of the resulting analysis

2.5 Commonly Used Wavelet Families

There are many wavelet families so far invented and some commonly used wavelet families are:

Table 2.1: Commonly used wavelet functions

Wavelet Family Short Name	Wavelet Family Name
haar	Haar
db	Daubechies
sym	Symlet
coif	Coiflet
bior	Biorthogonal
rbio	Reverse biorthogonal
morl	Morlet wavelet
cgau	Complex Gaussian
shan	Shannon

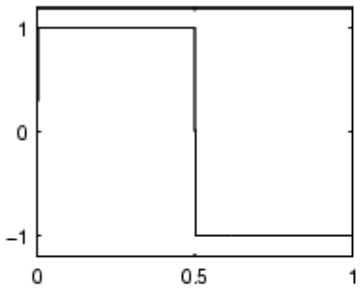
2.6 Wavelets Used in this Study

In this study, we have considered five wavelets families and selected one mother wavelet function from each were for the classification of ECG beats.

Table 3.2: Wavelet functions used in our study

Wavelet Family	Selected Wavelet
Haar	*haar*
Daubechies	*db10*
Biorthogonal	*bior 6.8*
Coiflet	*coif2*
Symlet	*sym4*

2.6.1 Haar Wavelet



The haar wavelet was created by Alfred Haar in 1909 .It is the first, simplest, and one of the most widely used wavelets. Haar wavelet is discontinuous, and resembles a step function as shown in figure. It represents the same wavelet as Daubechies 1(db1).

The haar wavelet can be represented as:

$$W(x) = \begin{cases} 1, & 0 \leq t < 0.5 \\ -1, & 0.5 \leq t < 1 \\ 0, & else \end{cases}$$

Technical disadvantage of haar wavelet is that due to discontinuity, no derivative form is available. For haar wavelets:

- *Support width=1*
- *Filters length=2*

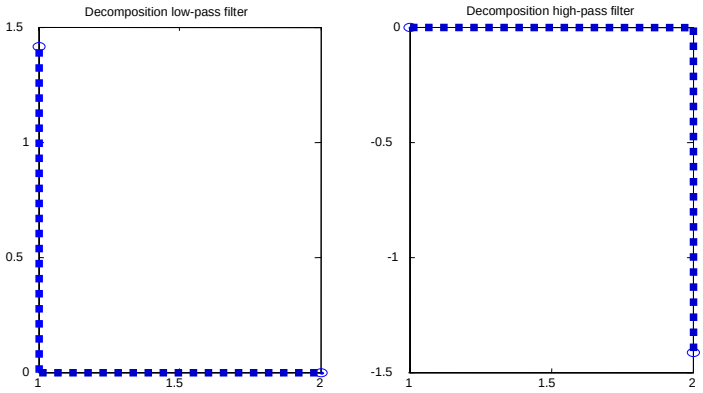
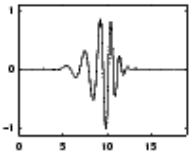


Figure 2.2: Decomposition low-pass and high-pass filters for haar wavelet

2.6.2 Daubechies Wavelet


db10

Ingrid Daubechies, one of the pioneers in the field of wavelet research, invented the Daubechies family which are called compactly supported orthonormal wavelets thus making discrete wavelet analysis practicable. The names of the Daubechies family wavelets are written dbN,where N is the order, and db the "surname" of the wavelet.

The db1 wavelet, as mentioned above, is the same as haar wavelet. Associated scaling filters are minimum-phase filters. Daubechies wavelets are obtained in different orders. Such as: db1 or haar, db2, db3, db7, db10 etc. In our study we have used db10. For the Daubechis family:

- *Support width=2N-1*
- *Filters length=2N*

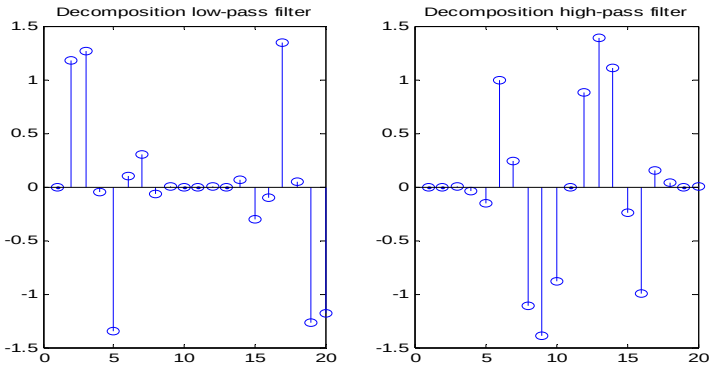
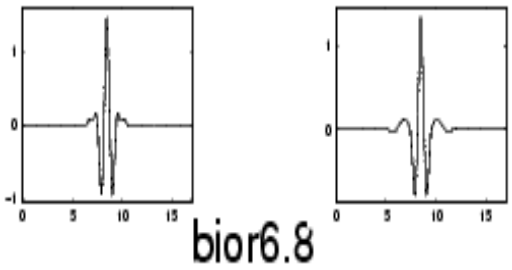


Figure 2.3: Decomposition low-pass and high-pass filters for db10 wavelet

2.6.3 Bi-orthogonal Wavelet


bior6.8

This family of wavelets exhibits the property of linear phase, which is needed for signal and image reconstruction. By using two wavelets, one for decomposition (shown on the left side in the figure) and the other for reconstruction (shown on the right side) instead of the same single one, interesting properties are derived. Some examples of this family are bior1.1, bior5.5, bior6.8 etc.

In our study we have used bior6.8.

For the Biorthogonal family:

- *Support width=2Nr+1 for reconstruction, 2Nd+1 for decomposition*
- *Filters length=max(2Nr,2Nd)+2*

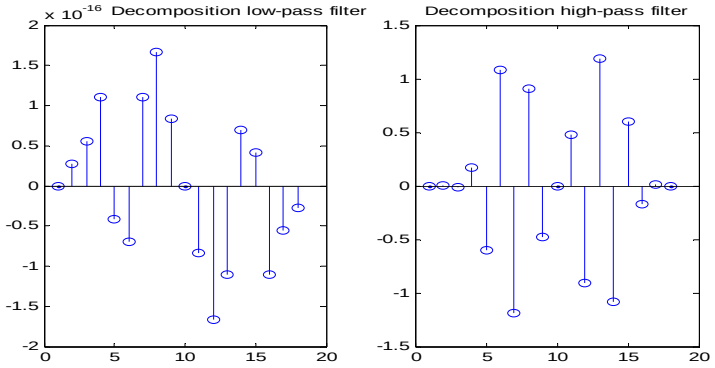
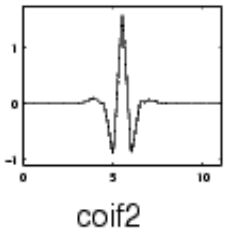


Figure 2.4: Decomposition low-pass and high-pass filters for bior6.8 wavelet

2.6.4 Coiflet Wavelet

Ronald Coifman was the first to suggest the construction of an orthonormal wavelet family with vanishing moments for both the wavelet and scaling functions. This led to the creation of the Coiflet family, built by I. Daubechies at the request of Coifman. It is denoted



by coifN, where N is the order and coif is the family name of wavelet. Some examples of this family are: coif1, coif2, coif3, coif4, coif5 etc.

In our study we have used coif2. For the Coiflet family:

- *Support width=6N-1*
- *Filters length=6N*

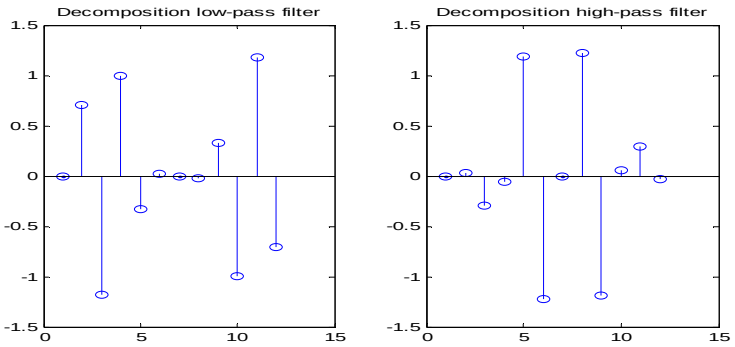
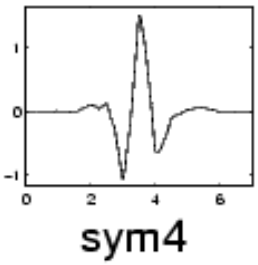


Figure 2.5: Decomposition low-pass and high-pass filters for coif2 wavelet

2.6.5 Symlet Wavelet

Symlet wavelets are nearly symmetrical wavelets proposed by Daubechies as modifications to the db family. The properties of the two wavelet families are quite similar. The wavelets of the Symlet family are denoted as symN, where N is the order of the wavelet. Some examples of this family are: sym2, sym4, sym5, sym8 etc. In our study we have used sym4. For the Symlet family:



- *Support width=2N-1*
- *Filters length=2N*

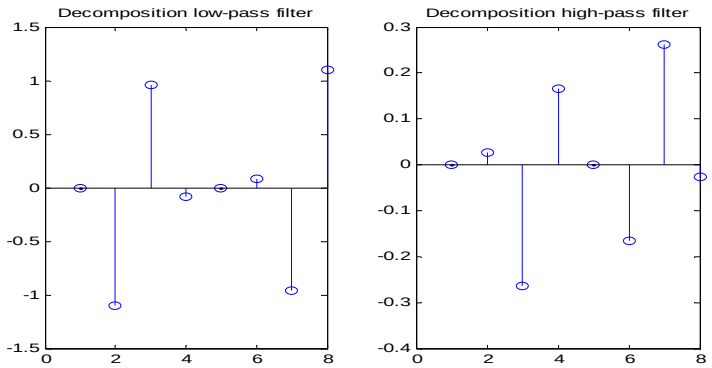


Figure 2.6: Decomposition low-pass and high-pass filters for sym4 wavelet

Chapter 3
ELECTROCARDIOGRAM

3.1 Anatomy and Physiology of Human Heart

Heart is one of the most vital organs in human body. It is a muscular organ located in the chest (thoracic) cavity between the right and left lungs. The size of the heart can vary depending on one's age, size, and the condition of the heart. Some diseases of the heart can cause it to become larger or smaller.

Human heart is divided longitudinally into right and left halves, each consisting of two chambers, an atrium and a ventricle. The cavities of the atrium and ventricle on each side of the heart communicate with each other but the right chambers do not communicate directly with those on the left. Thus the right and left ventricles are distinct. Some of the main blood vessels—arteries and veins—that make up blood circulatory system are directly connected to the heart. The ventricles on the right side of the heart pumps blood from heart to the lungs. When we breathe air in, then oxygen passes from lungs through the blood vessels and into the blood. Carbon dioxide, a waste product, is passed from our blood through blood vessels to lungs and is removed from the body when we breathe out. The left atrium receives oxygen-rich blood from the lungs. The pumping action of the left ventricle sends this oxygen-rich blood through the aorta to the rest of the body.

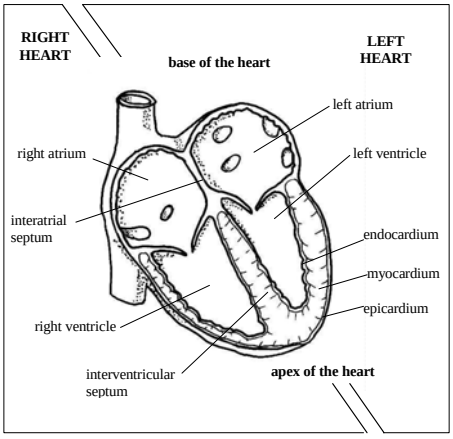


Figure 3.1: Anatomy of the heart

The right and left sides of the heart are divided by an internal wall of tissue called the septum. The area of the septum that divides the atria (the two upper chambers of your heart) is called the atrial or interatrial septum. The area of the septum that divides the ventricles (the two lower chambers of your heart) is called the ventricular or interventricular septum. The two septa, in effect, divide the heart into two pumping systems, the right heart and the left heart, each one consisting of an atrium and a ventricle. Below is a picture of the inside of a normal, healthy, human heart:

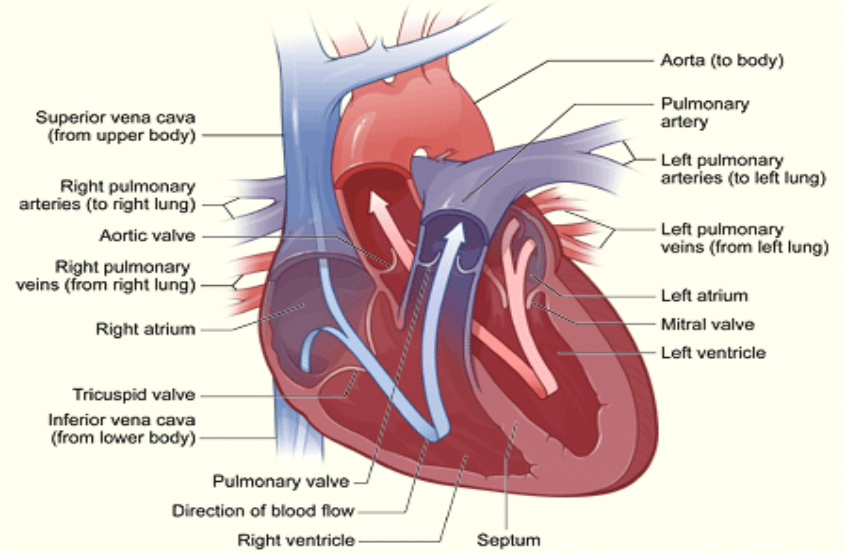


Figure 3.2: Cross-section of a healthy heart and its inside structures.

3.2 Electrical Activity of the Heart

The electrical conduction system of the heart is composed of the following structures: Sinoatrial (SA) node, Internodal atrial conduction tracts and the interatrial conduction tract (Bachmann's bundle), Atrioventricular (AV) junction consisting of the atrioventricular (AV) node and bundle of His, right bundle branch, left bundle branch, and left anterior and posterior fascicles, Purkinje network.

The prime function of the electrical conduction system of the heart is to transmit minute electrical impulses from the SA node (where they are normally generated) to the atria and ventricles, causing them to contract. The SA node lies in the wall of the right atrium near the inlet of the superior vena cava. It consists of pacemaker cells that generate electrical impulses automatically and regularly.

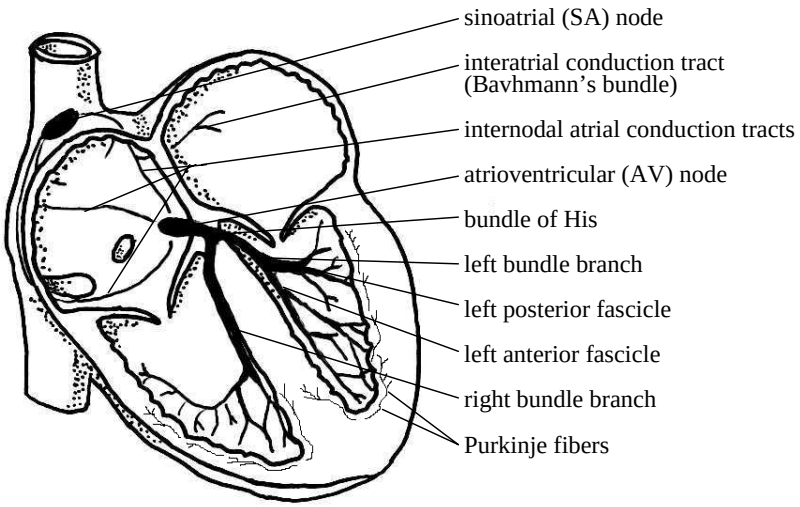


Figure 3.3: Electrical conduction system of the heart

The three internodal atrial conduction tracts, running through the walls of the right atrium between the SA node and the AV node, conduct the electrical impulses rapidly from the SA node to the AV node in about 0.03 second. The interatrial conduction tract (Bachmann's bundle), a branch of one of the internodal atrial conduction tracts, extends across the atria, conducting the electrical impulses from the SA node to the left atrium.

The AV node lies partly in the right side of the interatrial septum in front of the opening of the coronary sinus and partly in the upper part of the interventricular septum above the base of the tricuspid valve. The primary function of the AV node is to relay the electrical impulses from the atria into the ventricles in an orderly and timely way. A ring of fibrous tissue insulates the reminder of the atria from the ventricles, preventing electrical impulses from entering the ventricles except through the AV node. The electrical impulses slow as they travel through the AV node, taking about 0.06 to 0.12 second to reach the bundle of His. The delay is such that the atria can contract and empty, and the ventricles fill before they are stimulated to contract.

The bundle of His lies in the upper part of the interventricular septum, connecting to the AV node with two bundle branches. Once the electrical impulses enter the bundle of His, they travel more rapidly on their way to the bundle branches, taking 0.03 to 0.05 second. The electrical impulses travel very rapidly to the Purkinje network through the bundle

branches in less than 0.01 second. All in all, it normally takes the electrical impulses less than 0.2 second to travel from the SA node to the Purkinje network in the ventricles.

3.3 Arrhythmia

The rhythm of the heart is normally generated and regulated by pacemaker cells within the sinoatrial (SA) node, which is located within the wall of the right atrium. SA nodal 6 pacemaker activity normally governs the rhythm of the atria and ventricles. Normal rhythm is very regular, with minimal cyclical fluctuation. Furthermore, atrial contraction is always followed by ventricular contraction in the normal heart. When this rhythm becomes irregular, too fast (tachycardia) or too slow (bradycardia), or the frequency of the atrial and ventricular beats are different, this is called an arrhythmia. The term “dysrhythmia” is sometimes used and has a similar meaning. About 14 million people in the USA have arrhythmias (5% of the population). The most common disorders are atrial fibrillation and flutter. The incidence is highly related to age and the presence of underlying heart disease; the incidence approaches 30% following open heart surgery. Patients may describe an arrhythmia as a palpitation or fluttering sensation in the chest.

For some types of arrhythmias, a skipped beat might be sensed because the subsequent beat produces a more forceful contraction and a thumping sensation in the chest. A "racing" heart is another description. Proper diagnosis of arrhythmias requires an electrocardiogram, which is used to evaluate the electrical activity of the heart. Depending on the severity of the arrhythmia, patients may experience dyspnea (shortness of breath), syncope (fainting), fatigue, heart failure symptoms, chest pain or cardiac arrest. A frequent cause of arrhythmia is coronary artery disease because this condition results in myocardial ischemia or infarction. When cardiac cells lack oxygen, they become depolarized, which lead to altered impulse formation and/or altered impulse conduction. The former concerns changes in rhythm that are caused by changes in the automaticity of pacemaker cells or by abnormal generation of action potentials at sites other than the SA node (termed ectopic-foci). Altered impulse conduction is usually associated with complete or partial block of electrical conduction within the heart. Altered impulse conduction commonly results in reentry, which can lead to tachy-arrhythmias. Changes in cardiac structure that accompany heart failure (e.g., dilated or hypertrophied cardiac chambers) can also precipitate arrhythmias.

Finally, many different types of drugs (including anti-arrhythmic drugs) as well as electrolyte disturbances (primarily K+ and Ca++) can precipitate arrhythmias. Arrhythmias can be either benign or more serious in nature depending on the hemodynamic consequence of the arrhythmia and the possibility of evolving into a lethal arrhythmia. Occasional premature ventricular complexes (PVCs), while annoying to a patient, are generally considered benign because they have little hemodynamic effect. Consequently, PVCs if not too frequent, are generally not treated. In contrast, ventricular 7 tachycardia is a serious condition that can lead to heart failure, or worse, to ventricular fibrillation and death. When arrhythmias require treatment, they are treated with drugs that suppress the arrhythmia. These drugs are called anti-arrhythmic drugs. There are many different types of anti-arrhythmic drugs and many different mechanisms of action. Most of the drugs affect ion channels that are involved in the movement of sodium, calcium and potassium ions in and out of the cell. These drugs include mechanistic classes such as sodium-channel blockers, calcium-channel blockers and potassium-channel blockers. By altering the movement of these important ions, the electrical activity of the cardiac cells (both pacemaker and non-pacemaker cells) is altered, hopefully in a manner that suppresses arrhythmias. Other drugs affect autonomic influences on the heart, which may be stimulating or aggravating arrhythmias.

3.4 Electrocardiogram

Electrocardiography (ECG or EKG) is a graphic interpretation of the electrical activity of the heart over time captured and externally recorded by skin electrodes. ECGs are obtained by a machine known as electrocardiograph, which captures the ECG signal through an array of electrode sensors known as leads. They are placed at standard locations on the human skin. This display indicates the overall rhythm of the heart and weaknesses in different parts of the heart muscle. It is the best way to measure and diagnose abnormal rhythms of the heart.

3.4.1 Basic Components of ECG

ECG is a graphic record of the changes in magnitude and direction of the electrical activity, or, more specifically, the electric current that is generated by the depolarization and repolarization of the atria and ventricles. A typical signal from one ECG lead is quasi-periodic with periodicity of about one second. Within one period, called a cardiac cycle,

the ECG is comprised of 4 to 5 unique bumps of different characteristics. This pattern of bumps, known as waves, represents the electrical activity coordinating the series of muscle contraction that makes one heart beat .The electric current generated by atrial depolarization is recorded as the P wave, and that generated by ventricular depolarization is recorded as the Q, R, and S waves: the QRS complex .

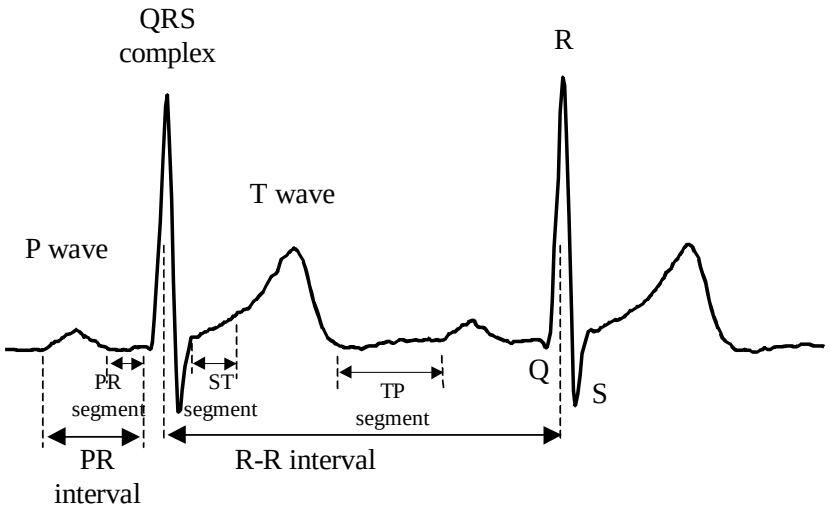


Figure 3.4: Components of the ECG

In a normal cardiac cycle, the P wave occurs first, followed by the QRS complex and the T wave. When electrical activity of the heart is not being detected, the ECG is a straight, flat line –the isoelectric line or baseline.

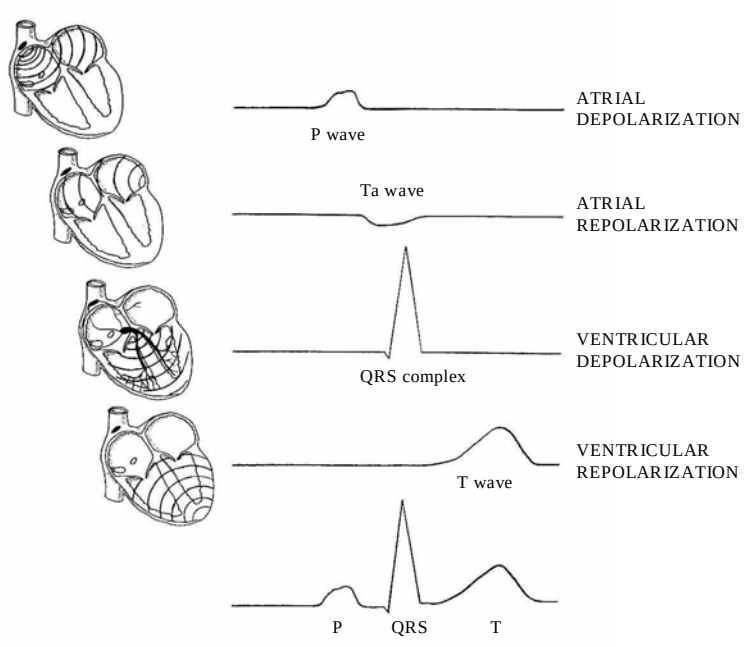


Figure 3.5: Electrical basis of the ECG

The following table presents the characteristics of different components of the ECG signal.

Table 3.1: Characteristics of ECG signal components

P wave	During normal atrial depolarization, the main electrical vector is directed from the SA node towards the AV node, and spreads from the right atrium to the left atrium. This turns into the P wave on the ECG.
QRS complex	The QRS complex is a recording of a single heartbeat on the ECG that corresponds to the depolarization of the right and left ventricles.
PR interval	The PR interval is measured from the beginning of the P wave to the beginning of the QRS complex.
ST segment	The ST segment connects the QRS complex and the T wave.
T wave	The T wave represents the repolarization (or recovery) of the ventricles. The interval from the beginning of the QRS complex to the apex of the T wave is referred to as the absolute refractory period. The last half of the T wave is referred to as the relative refractory period (or vulnerable period).
QT interval	The QT interval is measured from the beginning of the QRS complex to the end of the T wave.
U wave	The U wave is not always seen. It is typically small, and, by definition, follows the T wave.

Normal values of ECG Parameters:

Heart rate: 120 beats per minute (BPM)

Amplitude:

P wave:	0.25mV
R wave	1.60mV
Q wave	25% of R wave
T wave	0.1 to 0.5mV

Duration:

PR interval	0.12 to 0.20 sec
QT interval	0.35 to 0.44 sec
ST interval	0.05 to 0.15 sec
P wave interval	0.11 sec
QRS interval	0.09 sec

3.4.2 ECG Monitoring Method

Electrodes are placed on designated areas of the patient's body, and these various combinations of the electrodes are used for analysis of the heart condition. Each separate view of the heart is called an ECG lead. The two ECG monitoring methods are standard 12-lead ECG monitoring and continuous ECG monitoring or holter monitoring. 12-lead ECG consists of three standard leads, designated as lead I,II,III and three augmented leads, designated as lead a VR, a VL and a VF, that view the heart in the frontal plane, and six pre-cordial or chest leads, designated V1 throughV2, that view the heart in the horizontal plane. Both the standard leads and the augmented leads are limb leads. The standard leads are called bipolar because they are composed of two electrodes-one that is negative and one that is positive-and the ECG records the difference in electrical potential between them. The standard 12-lead ECG records 12 different views of the same electrical activity on the ECG graph paper. Holter monitoring provides a continuous recording of heart rhythm during normal activity, and the monitor is usually worn for 24 hours. In holter monitoring, electrodes (small conducting patches) are placed on the chest and attached to a small recording monitor that can be carried or in a small pouch worn around the neck.

3.4.3 Normal ECG Signal

The normal ECG waves are following ------

Normal sinus rhythm:

– Each P wave is followed by a QRS complex.

– P wave rate is 60~100 beats per minute bpm). If rate is less than 60 bpm, it is called sinus bradycardia. If rate is greater than 100, it is called sinus tachycardia.

Normal P waves:

– Height is less than 2.5 mm in lead II

– Width is less than 0.11 s in lead II

Normal PR interval

– 0.12 to 0.20 s (3-5 small squares)

Normal QRS complex:

– Less than 0.12 s duration (3 small squares)

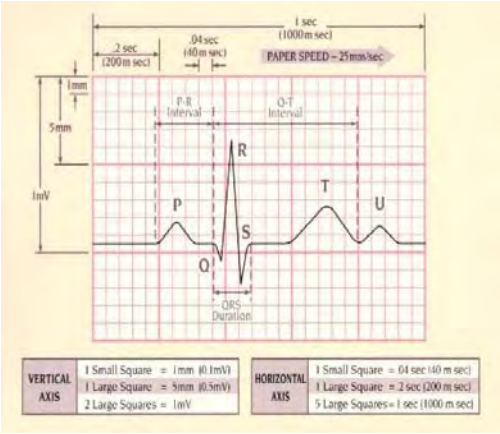


Figure 3.6: Normal ECG Signal

Normal QT interval :

– Calculate the corrected QT interval by dividing the QT interval by the square root of the proceeding R-R interval. Normal is 0.42 s.

Normal ST segment:

– No elevation or depression

3.5 Cardiac Phenomena in Consideration

In our study we have considered five particular types of cardiac phenomena. A brief description of these phenomena are given below:

3.5.1 Normal Beat

Normal beat means normal cardiac state. A state in which there is not any significant existence of any kind of abnormality. Such state is normally seen in healthy persons. The ECG corresponding ECG waveshape has the normal pattern.

3.5.2 Left Bundle Branch Block (LBBB)

Left bundle branch block occurs due to the failure of the left bundle branch to transmit excitation. Excitation of the ventricular myocardium develops in an orderly manner because of the conduction system, which consists of the A-V node, Bundle-of-His (with left and right branches) and Purkinje fibers. This conduction system has a propagation velocity that is higher than in ventricular muscle. The net result is that both ventricular contract almost simultaneously and the beat that results develops the maximum force. Left bundle branch block causes delay of excitation in the left ventricle and excitation travels generally from right to left. Common criterion in ECG wave shapes for left bundle branch block:

- The QRS duration must be = or > 120 ms
- There should be a QS or rS complex in lead V1
- There should be a monophasic R wave and no Q wave in leads I and V6.

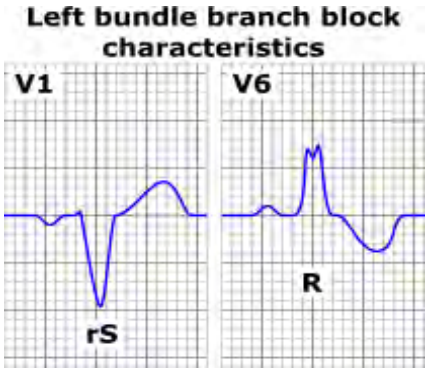


Fig. 3.7: LBBB Characteristics

3.5.3 Right Bundle Branch Block (RBBB)

Right bundle branch block occurs due to the failure of the right bundle branch to transmit excitation. A block of excitation in one of the branches causes the affected side to be

excited or depolarized late and this fact is revealed in a prolongation of the duration of the QRS. So in case of right bundle branch block there is delay of excitation in the right ventricle and excitation travels generally from left to right. Criteria for left bundle branch block:

- The QRS duration must be more than 100 ms (incomplete block) or more than 120 ms (complete block)
- There should be a terminal R wave in lead V1
- There should be a slurred S wave in leads I and V6.

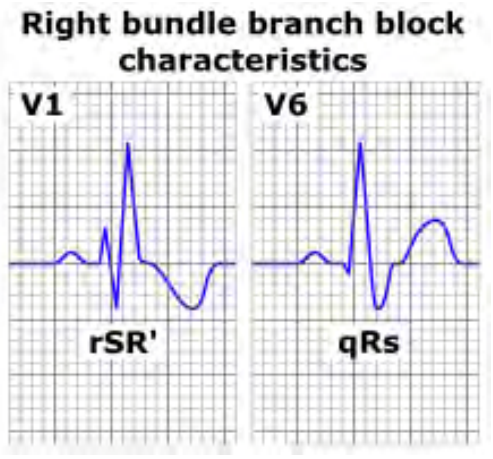


Figure 3.8: RBBB Characteristics

3.5.4 Premature Ventricular Contraction (PVC)

Premature ventricular contraction (PVC), also known as ventricular premature beat (VPB) or extra systole is a relatively common condition where the heartbeat is initiated by the heart ventricles rather than the sinoatrial node; the normal heartbeat initiator .This may be perceived as a “skipped beat” or felt as palpitations in the chest. In a normal heartbeat, the ventricles contract after the atria, forcing blood both to the body and to the lungs. In case of PVC, the ventricles contract first which means that circulation is inefficient. However, single beat PVC arrhythmias do not usually pose a danger and can be asymptomatic in healthy individuals. PVC can occur in a healthy person of any age, but becomes more frequent in the elderly, and is more commonly found in men.

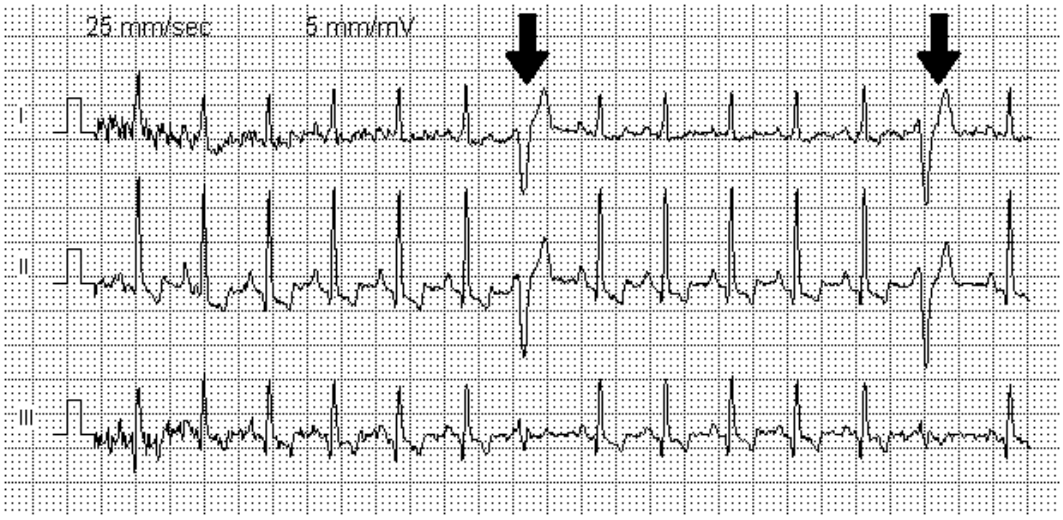


Figure 3.9: PVC characteristics

3.5.5 Atrial Premature Beat (APB)

The term atrial premature beat describes beats arising from the atrium and occurring before the expected sinus beats. Premature beats can occur randomly or in a pattern. Premature atrial beats generally depolarize and reset the sinus node so that the next sinus beat occurs sooner than the expected sinus P wave. Expressed differently, the interval from sinus atrial premature beat plus the next sinus beat measures less than two sinus cycles. This phenomenon, incomplete compensatory pause, is fairly common with atrial premature beats.

Atrial premature beats are slightly less frequent than ventricular premature beats, but much more frequent than supraventricular premature beats arising in the atrio-ventricular (AV) junction. Often APBs are not associated with heart disease. In up to 64% of healthy young individuals, some APBs are found in an ambulatory electrocardiogram (Holter ECG), and in most cases without symptoms. It has been empirically noted that alcohol in excess, fatigue, cigarettes, fever, anxiety and infectious diseases of all sort may result in atrial premature beats, and elimination of these factors may correct the disorder. Atrial premature beats also occur in some patients with myocardial ischemia, pulmonary disease and systemic hypoxia.

Premature beats are usually perceived by patients as “palpitations”, and sometimes are of concern to patients who notice “skipped” beats or “fluttering” that are frightening. Often

atrial premature beats cause no symptoms and are not recognized by the patient. Atrial premature beats require no specific therapy If they are a source of aggravation or concern to the patient and one of the above-mentioned factors can be identified and easily corrected, then that should be done.

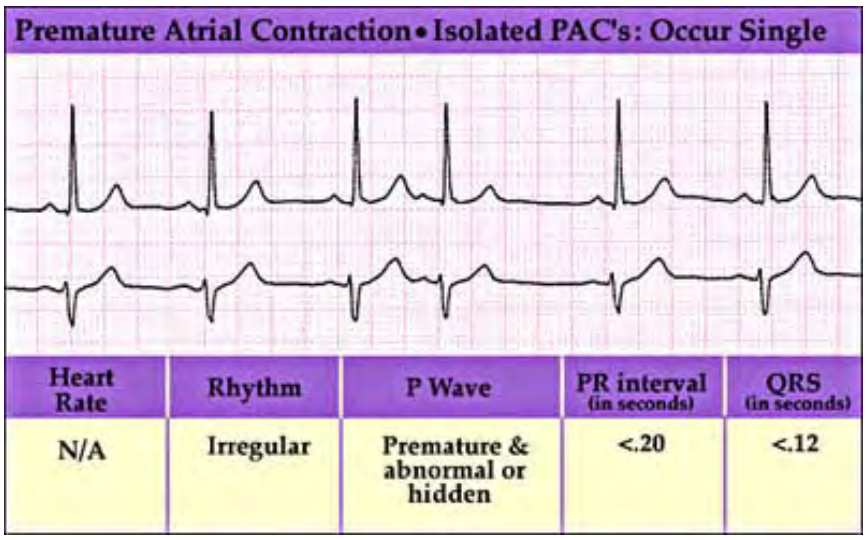


Figure 3.10: APB characteristics

Chapter 4
RESULTS

4.1 Selection Criteria

The source of the ECGs included in the MIT-BIH arrhythmia database is a set of over 4000 long-term Holter recordings that were obtained by the Beth Israel Hospital Arrhythmia Laboratory between 1975 and 1979. Approximately 60% of these recordings were obtained from inpatients. The database contains 23 records chosen at random from this set, and 25 records selected from the same set to include a variety of rare but clinically important phenomena that would not be well-represented by a small random sample of Holter recordings. Each of the 48 records is slightly over 30 minutes long.

The first group is intended to serve as a representative sample of the variety of waveforms and artifact that an arrhythmia detector might encounter in routine clinical use. A table of random numbers was used to select tapes, and then to select half-hour segments of them. Segments selected in this way were excluded only if neither of the two ECG signals was of adequate quality for analysis by human experts. Records in the second group were chosen to include complex ventricular, junctional, and supraventricular arrhythmias and conduction abnormalities. Several of these records were selected because features of the rhythm, QRS morphology variation, or signal quality may be expected to present significant difficulty to arrhythmia detectors; these records have gained considerable notoriety among database users. The subjects were 25 men aged 32 to 89 years, and 22 women aged 23 to 89 years.

4.2 Analog Recording and Digitization

The original analog recordings were made using nine Del Mar Avionics model 445 two-channel recorders. The analog outputs of the playback unit were filtered to limit analog-to-digital converter (ADC) saturation and for anti-aliasing, using a passband from 0.1 to 100 Hz relative to real time, well beyond the lowest and highest frequencies recoverable from the recordings. The bandpass-filtered signals were digitized at 360 Hz per signal relative

to real time using hardware constructed at the MIT Biomedical Engineering Center and at the BIH Biomedical Engineering Laboratory.

The sampling frequency was chosen to facilitate implementations of 60 Hz (mains frequency) digital notch filters in arrhythmia detectors. Since the recorders were battery-powered, most of the 60 Hz noise present in the database arose during playback. In those records that were digitized at twice real time, this noise appears at 30 Hz (and multiples of 30 Hz) relative to real time. Samples were acquired from each signal almost simultaneously (the intersignal sampling skew was on the order of a few microseconds). As noted above, analog tape skew was several orders of magnitude larger. The ADCs were unipolar, with 11-bit resolution over a ±5 mV range. Sample values thus range from 0 to 2047 inclusive, with a value of 1024 corresponding to zero volts. The 11-bit samples were originally recorded in 8-bit first difference format (this was necessary because of limited mass storage capacity). Given the sampling frequency and the resolution of the ADC, the difference encoding implies a maximum recordable slew rate of ±225 mV/s.

4.3 Contents of the Database

The following table summarizes the contents of the MIT-BIH Arrhythmia Database.

Table 4.1: MIT-BIH Arrhythmia Database

	N							**V**	**F**	**O**	**N**		**E**	**P**	**F**	**O**	**Q**
Record	**.**	**L**	**R**	**A**	**a**	**J**	**S**	**V**	**F**	**!**	**e**	**j**	**E**	**P**	**f**	**p**	**Q**
100	2239	-	-	33	-	-	-	1	-	-	-	-	-	-	-	-	-
101	1860	-	-	3	-	-	-	-	-	-	-	-	-	-	-	-	2
102	99	-	-	-	-	-	-	4	-	-	-	-	-	2028	56	-	-
103	2082	-	-	2	-	-	-	-	-	-	-	-	-	-	-	-	-
104	163	-	-	-	-	-	-	2	-	-	-	-	-	1380	666	-	18
105	2526	-	-	-	-	-	-	41	-	-	-	-	-	-	-	-	5
106	1507	-	-	-	-	-	-	520	-	-	-	-	-	-	-	-	-
107	-	-	-	-	-	-	-	59	-	-	-	-	-	2078	-	-	-
108	1739	-	-	4	-	-	-	17	2	-	-	1	-	-	-	11	-
109	-	2492	-	-	-	-	-	38	2	-	-	-	-	-	-	-	-

Table 4.1: MIT-BIH Arrhythmia Database (Contd)

	N							V	F	O	N		E	P	F	O	Q
Record	.	L	R	A	a	J	S	V	F	!	e	j	E	P	f	p	Q
111	-	2123	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-
112	2537	-	-	2	-	-	-	-	-	-	-	-	-	-	-	-	-
113	1789	-	-	-	6	-	-	-	-	-	-	-	-	-	-	-	-
114	1820	-	-	10	-	2	-	43	4	-	-	-	-	-	-	-	-
115	1953	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
116	2302	-	-	1	-	-	-	109	-	-	-	-	-	-	-	-	-
117	1534	-	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-
118	-	-	2166	96	-	-	-	16	-	-	-	-	-	-	-	10	-
119	1543	-	-	-	-	-	-	444	-	-	-	-	-	-	-	-	-
121	1861	-	-	1	-	-	-	1	-	-	-	-	-	-	-	-	-
122	2476	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
123	1515	-	-	-	-	-	-	3	-	-	-	-	-	-	-	-	-
124	-	-	1531	2	-	29	-	47	5	-	-	5	-	-	-	-	-
200	1743	-	-	30	-	-	-	826	2	-	-	-	-	-	-	-	-
201	1625	-	-	30	97	1	-	198	2	-	-	10	-	-	-	37	-
202	2061	-	-	36	19	-	-	19	1	-	-	-	-	-	-	-	-
203	2529	-	-	-	2	-	-	444	1	-	-	-	-	-	-	-	4
205	2571	-	-	3	-	-	-	71	1	-	-	-	-	-	-	-	-
207	-	1457	86	99	-	-	-	105	-	-	-	-	-	105	-	-	-
208	1586	-	-	-	-	-	2	992	373	-	-	-	-	-	-	-	2
209	2621	-	-	383	-	-	-	1	-	-	-	-	-	-	-	-	-
210	2423	-	-	-	22	-	-	194	10	-	-	-	1	-	-	-	-
212	923	-	1825	-	-	-	-	-	-	-	-	-	-	-	-	-	-
213	2641	-	-	25	3	-	-	220	362	-	-	-	-	-	-	-	-
214	-	2003	-	-	-	-	-	256	1	-	-	-	-	-	-	-	2
215	3195	-	-	3	-	-	-	164	1	-	-	-	-	-	-	-	-
217	244	-	-	-	-	-	-	162	-	-	-	-	-	1542	260	-	-
219	2082	-	-	7	-	-	-	64	1	-	-	-	-	-	-	133	-
220	1954	-	-	94	-	-	-	-	-	-	-	-	-	-	-	-	-
221	2031	-	-	-	-	-	-	396	-	-	-	-	-	-	-	-	-
222	2062	-	-	208	-	1	-	-	-	-	-	212	-	-	-	-	-
223	2029	-	-	72	1	-	-	473	14	-	16	-	-	-	-	-	-
228	1688	-	-	3	-	-	-	362	-	-	-	-	-	-	-	-	-
230	2255	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-
231	314	-	1254	1	-	-	-	2	-	-	-	-	-	-	-	2	-
232	-	-	397	1382	-	-	-	-	-	-	-	1	-	-	-	-	-
233	2230	-	-	7	-	-	-	831	11	-	-	-	-	-	-	-	-
234	2700	-	-	-	-	50	-	3	-	-	-	-	-	-	-	-	-

Used Symbols:

Symbol	Meaning
· *or* N	Normal beat
L	Left bundle branch block beat
R	Right bundle branch block beat
A	Atrial premature beat
a	Aberrated atrial premature beat
J	Nodal (junctional) premature beat
S	Supraventricular premature beat
V	Premature ventricular contraction
F	Fusion of ventricular and normal beat
!	Ventricular flutter wave
e	Atrial escape beat
j	Nodal (junctional) escape beat
E	Ventricular escape beat
f	Fusion of paced and normal beat
Q	Unclassifiable beat
P	Pause

Table 4.2: List of Symbols

4.4 Test Data

For the purpose of our study, we selected total 19 records from the MIT-BIH Arrhythmia Database. Each of these records indicates the presence of a particular type of cardiac phenomenon in the subject. Some information regarding these records and their subjects is given below:

Table 4.3: List of ECG records used in the study

Record No.	Cardiac Phenomena in Consideration	Subject
115	Normal Beat	Age 39, Female
117	Normal Beat	Age 69 ,Male
122	Normal Beat	Age 51,Male
230	Normal Beat	Age 32, Male
109	LBBB	Age 64, Male
111	LBBB	Age 47, Female
207	LBBB	Age 89, Female
214	LBBB	Age 53, Male
118	RBBB	Age 69, Male
124	RBBB	Age 77, Male
212	RBBB	Age 32, Female
231	RBBB	Age 72 ,Female
116	PVC	Age 68, Male
119	PVC	Age 51, Female
208	PVC	Age 23, Female
221	PVC	Age 83, Male
209	APB	Age 62, Male
220	APB	Age 87, Female
232	APB	Age 76, Female

Considering 2000 samples, sample plot of these records are given below:

4.4.1 Normal Beat

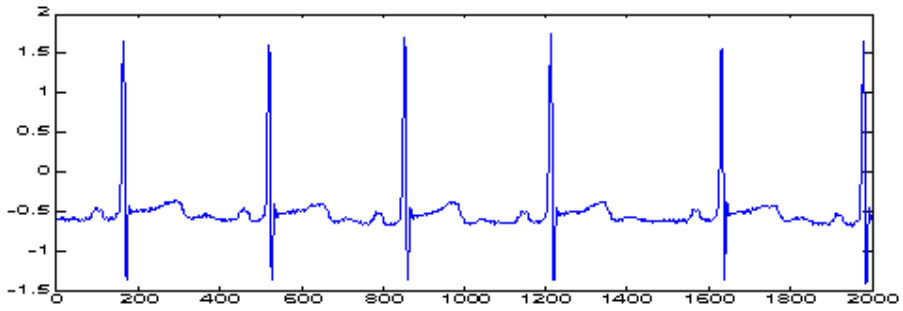


Figure 4.1: Record No. 115

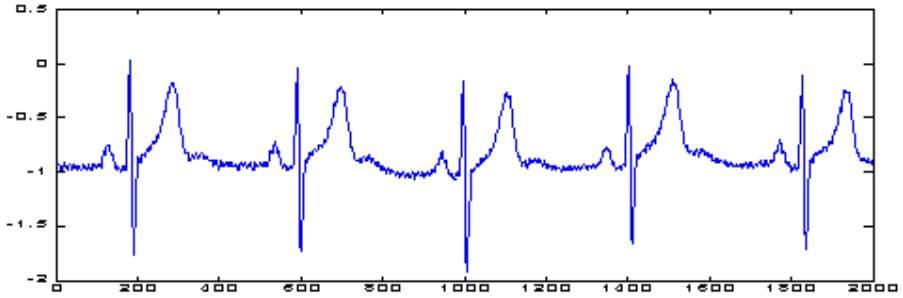


Figure 4.2: Record No. 117

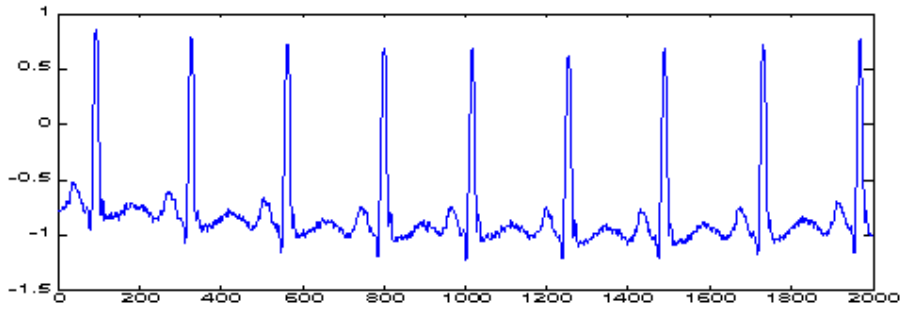


Figure 4.3: Record No. 122

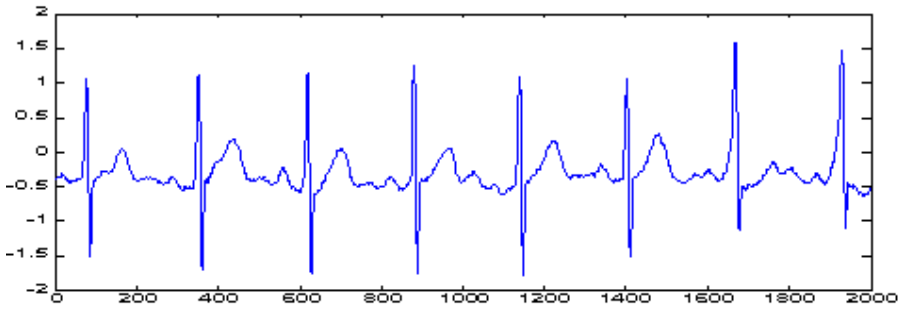


Figure 4.4: Record No. 230

4.4.2 Left Bundle Branch Block

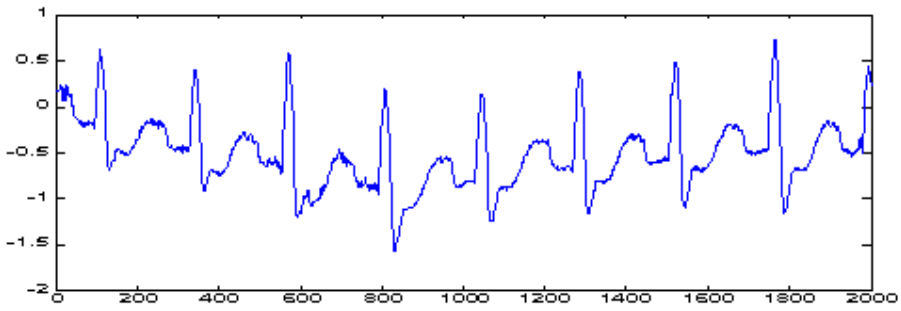


Figure 4.5: Record No. 109

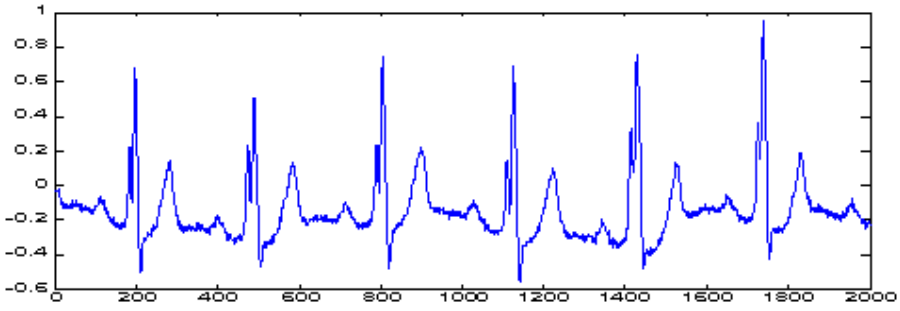


Figure 4.6: Record No. 111

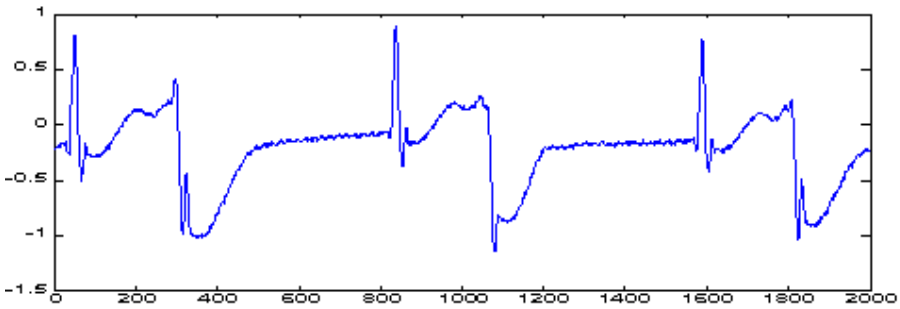


Figure 4.7: Record No. 207

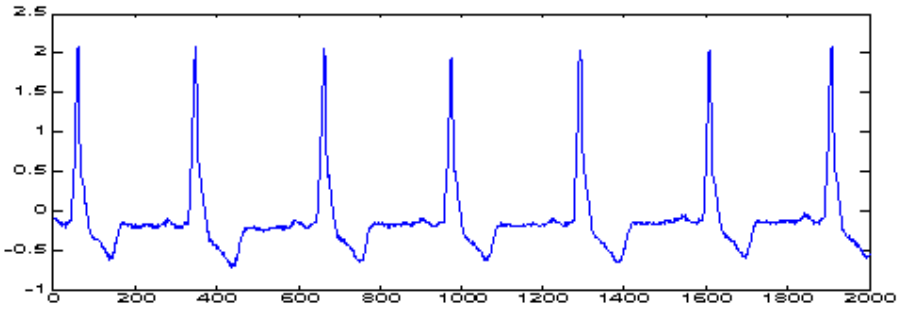


Figure 4.8: Record No. 214

4.4.3 Right Bundle Branch Block

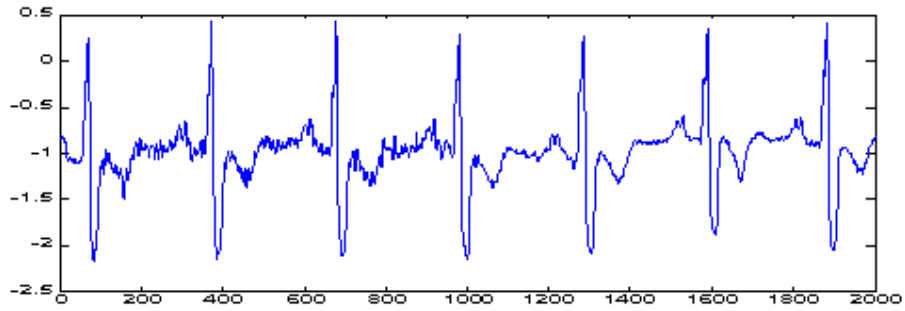


Figure 4.9: Record No. 118

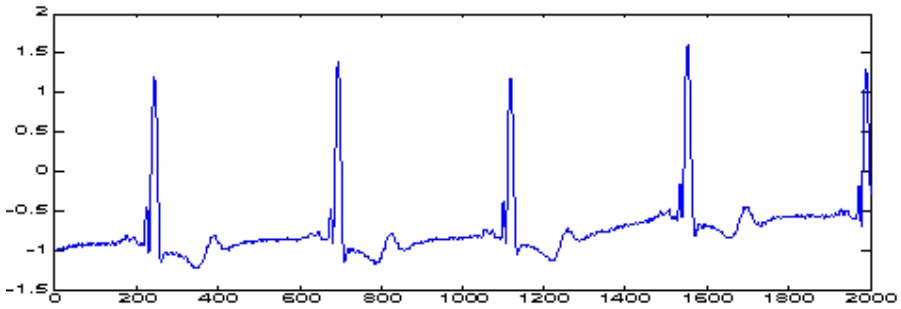


Figure 4.10: Record No. 124

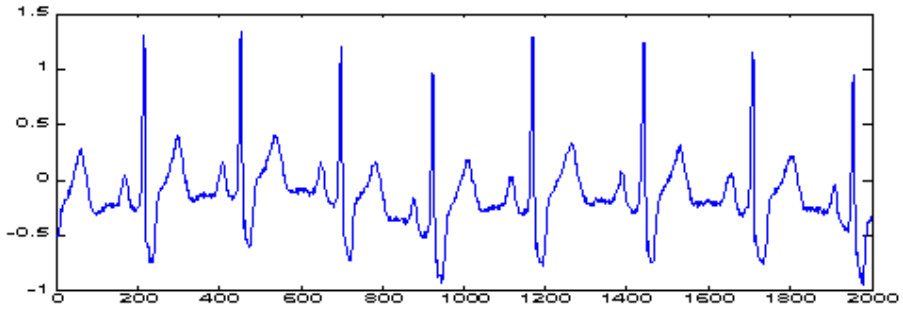


Figure 4.11: Record No. 212

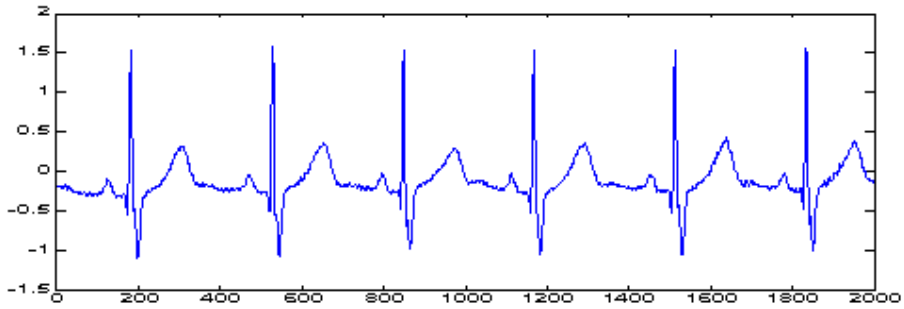


Figure 4.12: Record No. 231

4.4.4 Premature Ventricular Contraction

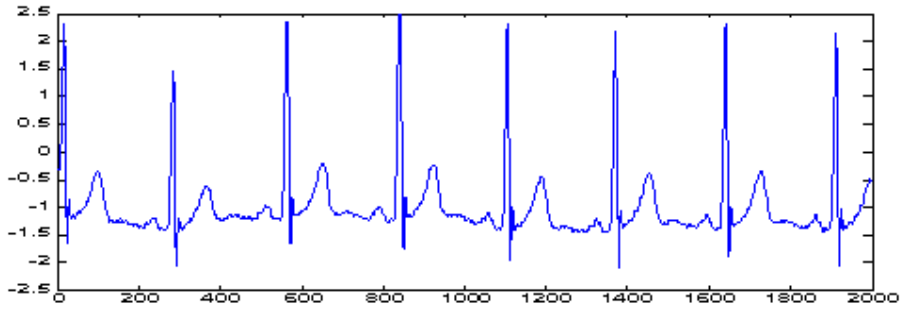


Figure 4.13: Record No. 116

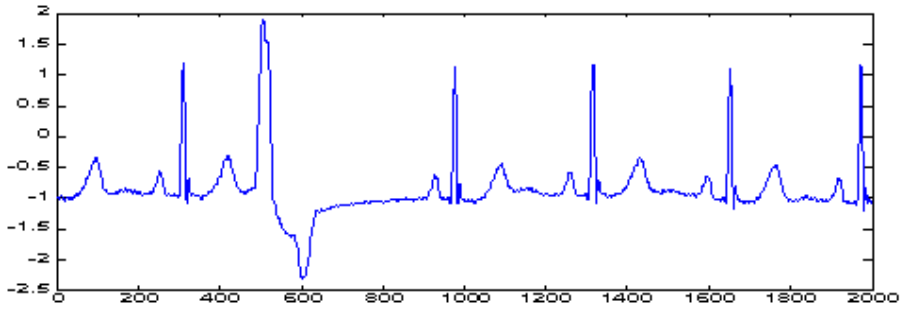


Figure 4.14: Record No. 119

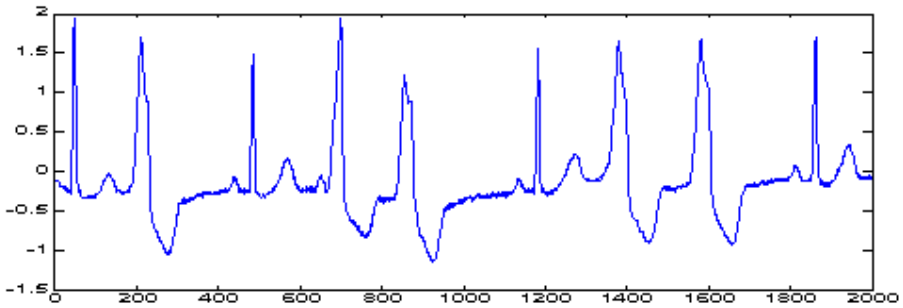


Figure 4.15: Record No. 208

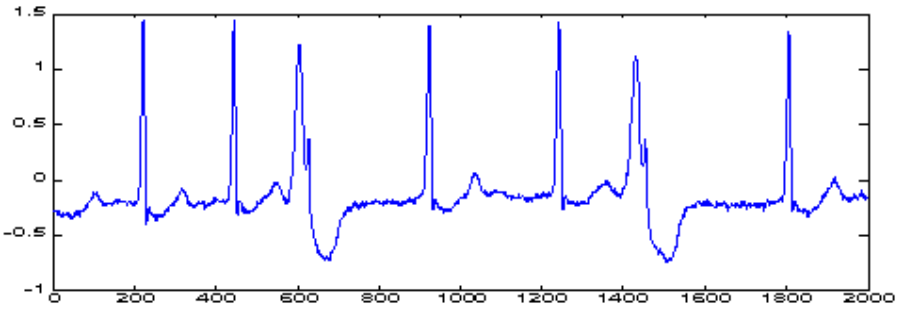


Figure 4.16: Record No. 221

4.4.5 Atrial Premature Beat

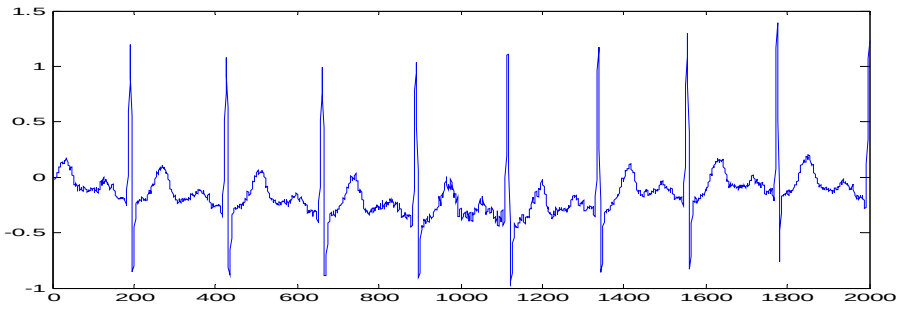


Figure 4.17: Record No. 209

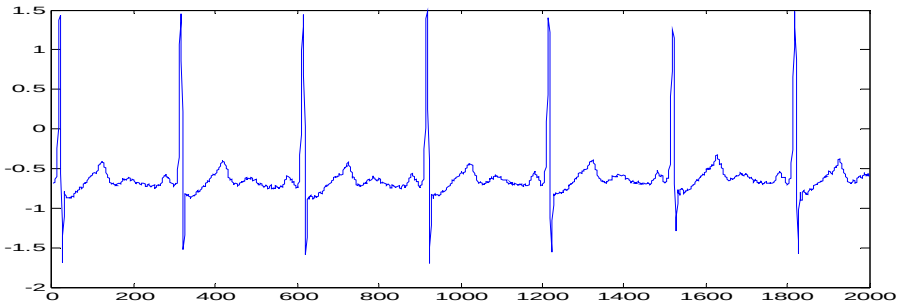


Figure 4.18: Record No. 220

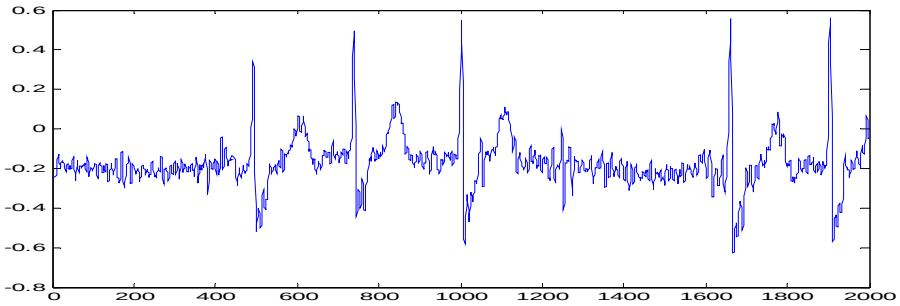


Figure 4.19: Record No. 232

4.5 Methodology

The whole analysis has been performed by codes written in Matlab 7.4.0 environment.

The procedure consists of the following steps:

1. Total number of samples to be used in the analysis, level of decomposition, and the mother wavelet function is defined by the user. In our study, we have worked with 40000 samples and 4^{th} level of decomposition.

2. ECG signals as obtained from the sample records are imported to Matlab and some initial processing of the raw data is performed.

3. Discrete Wavelet Transform (DWT) is performed on each of the records, based on the input parameters.

4. The results are calculated and displayed. Results include maximum, minimum, standard deviation and mean values of approximation coefficients of the final level and detail coefficients of each level.

5. For each of the cardiac phenomena, a plot of the range of values of A4 (max) is displayed.

4.6 Analysis Using haar

Selecting haar as the mother wavelet and performing an analysis up to level 4 with 40000 samples, the following results have been obtained:

4.6.1 Normal Beat

Table 4.4: Results obtained for normal beat using haar as the mother wavelet

Record No	Extracted Features	Subbands				
		D1	D2	D3	D4	A4
115	Maximum	0.4525	1.28	2.9946	4.3338	3.8075
	Minimum	-0.3005	-0.7625	-1.8084	-3.1638	-4.445
	Mean	0.00001	-2E-05	0.0001	-0.0023	-0.268
	Standard Deviation	0.0563	0.1068	0.1856	0.2098	0.813
117	Maximum	0.3394	0.6075	1.4743	2.5488	0
	Minimum	-0.1167	-0.315	-0.6929	-1.2563	-5.491
	Mean	-2E-05	0.0001	-2E-06	-0.0002	-0.409
	Standard Deviation	0.0262	0.0489	0.0879	0.1196	1.1195
122	Maximum	0.2581	0.6525	1.5327	2.8762	2.795
	Minimum	-0.1803	-0.475	-1.1968	-2.675	-8.371
	Mean	-4E-05	-1E-05	-0.0001	1E-05	-0.445
	Standard Deviation	0.039	0.0744	0.1337	0.2236	1.2636
230	Maximum	0.4525	1.21	3.037	4.6413	4.6913
	Minimum	-0.3147	-0.85	-1.6635	-2.4875	-6.321
	Mean	-0.0001	-0.0001	-0.00001	-0.0023	-0.077
	Standard Deviation	0.0544	0.1045	0.1816	0.2399	0.4712

4.6.2 Left Bundle Branch Block

Table 4.5: Results obtained for LBBB using haar as the mother wavelet

Record No	**Extracted Features**	**Subbands**				
		D1	**D2**	**D3**	**D4**	**A4**
109	Maximum	0.2121	0.5825	1.3135	2.78	4.875
	Minimum	-0.152	-0.365	-0.8397	-2.448	-6
	Mean	1E-06	3E-05	0.0002	0.0001	-0.13
	Standard Deviation	0.0328	0.0634	0.1204	0.2194	0.6418
111	Maximum	0.1273	0.31	0.769	1.8938	4.6075
	Minimum	-0.1273	-0.345	-0.7124	-1.176	-3.82
	Mean	0.0001	1E-05	0.00002	-1E-04	-0.084
	Standard Deviation	0.0221	0.0405	0.0699	0.1048	0.4084
207	Maximum	0.1485	0.425	0.9405	2.6925	4.8925
	Minimum	-0.1061	-0.2575	-0.5957	-1.359	-6.886
	Mean	-0.00001	1E-05	-4E-05	-1E-04	-0.071
	Standard Deviation	0.0198	0.0364	0.0663	0.115	0.5264
214	Maximum	0.3536	0.8575	1.6794	3.2488	6.3775
	Minimum	-0.2652	-0.705	-1.1756	-2.668	-7.146
	Mean	-0.00005	-0.0001	0.0001	0.0001	-0.1
	Standard Deviation	0.0403	0.0761	0.1336	0.2109	0.6453

4.6.3 Right Bundle Branch Block

Table 4.6: Results obtained for RBBB using haar as the mother wavelet

Record No	**Extracted Features**	**Subbands**				
		D1	**D2**	**D3**	**D4**	**A4**
118	Maximum	0.4384	1.1	2.6075	4.5738	3.2988
	Minimum	-0.1838	-0.45	-0.9245	-1.91	-9.88
	Mean	-0.0001	-0.00002	4E-05	0.0017	-0.475
	Standard Deviation	0.0487	0.093	0.1585	0.2667	1.3505
124	Maximum	0.2086	0.545	1.4407	3.3413	4.4
	Minimum	-0.251	-0.67	-1.7766	-3.231	-5.42
	Mean	-1E-05	-0.00002	-0.0001	0.0001	-0.407
	Standard Deviation	0.0348	0.0676	0.1259	0.1956	1.1665
212	Maximum	0.4278	1.0775	2.2627	3.0225	3.5863
	Minimum	-0.2864	-0.7575	-1.5167	-2.878	-3.951
	Mean	-0.0005	-0.00002	-0.0001	0.0003	-0.074
	Standard Deviation	0.04964	0.0932	0.1544	0.2099	0.4111
231	Maximum	0.4172	1.05	2.2345	3.0875	2.555
	Minimum	-0.3147	-0.8725	-1.9322	-3.138	-3.93
	Mean	0.00003	3E-06	0.0002	-0.002	-0.096
	Standard Deviation	0.0473	0.0892	0.1504	0.1913	0.4055

4.6.4 Premature Ventricular Contraction

Table 4.7: Results obtained for PVC using haar as the mother wavelet

Record No	**Extracted Features**	**Subbands**				
		D1	**D2**	**D3**	**D4**	**A4**
116	Maximum	0.4525	1.28	3.4595	5.9175	8.695
	Minimum	-0.4066	-1.075	-2.8001	-5.41	-8.815
	Mean	-0.0001	0.0002	-0.0001	0.0003	-0.4734
	Standard Deviation	0.0844	0.1623	0.286	0.3932	1.4299
119	Maximum	0.4172	1.0475	2.3105	4.1575	8.2138
	Minimum	-0.2934	-0.79	-1.9322	-3.4288	-9.8438
	Mean	-0.00002	0.00005	-0.0003	0.001	-0.4379
	Standard Deviation	0.0502	0.0964	0.1709	0.2487	1.3389
208	Maximum	0.3924	0.955	2.1779	3.5063	6.3725
	Minimum	-0.2899	-0.725	-1.6829	-2.695	-6.8413
	Mean	-0.0001	0.000001	0.00001	0.0023	-0.0552
	Standard Deviation	0.045	0.0855	0.1477	0.2176	0.6222
221	Maximum	0.2793	0.755	1.8897	3.0663	4.7275
	Minimum	-0.1768	-0.51	-1.1561	-2.47	-3.1438
	Mean	0.0001	-0.000003	0.000004	-0.0011	-0.0866
	Standard Deviation	0.0363	0.0688	0.1216	0.1694	0.4168

4.6.5 Atrial Premature Beat

Table 4.8: Results obtained for APB using haar as the mother wavelet

Record No	**Extracted Features**	**Subbands**				
		D1	**D2**	**D3**	**D4**	**A4**
209	Maximum	0.3818	1.13	2.0895	2.815	1.6025
	Minimum	-0.2333	-0.54	-1.4071	-2.155	-2.62
	Mean	-0.0001	-0.00004	-0.0002	-0.0002	-0.0801
	Standard Deviation	0.0482	0.0916	0.1489	0.184	0.2951
220	Maximum	0.4525	1.28	3.2474	4.6213	1.9363
	Minimum	-0.3429	-0.9775	-2.0188	-3.3088	-4.7788
	Mean	-0.0001	-0.00001	0.0005	0.0014	-0.2921
	Standard Deviation	0.0675	0.1279	0.2211	0.2561	0.8259
232	Maximum	0.2086	0.545	1.1932	1.7288	0.7513
	Minimum	-0.1414	-0.265	-0.6081	-1.1038	-2.3888
	Mean	0.00003	-0.0001	0.0003	-0.0002	-0.1003
	Standard Deviation	0.0215	0.0395	0.0664	0.0793	0.3027

4.6.6 Complete Result Obtained from the Analysis with haar

Table 4.9: A complete set of result obtained from the analysis with haar

ECG Beat Type	Extracted Features	Subbands				
	(Highest Values)	D1	D2	D3	D4	A4
Normal	Maximum	0.4525	1.28	3.037	4.6413	4.6913
	Minimum	-0.1167	-0.315	-0.6929	-1.2563	-4.445
	Mean	1E-05	0.0001	0.0001	1E-05	-0.077
	Standard Deviation	0.0563	0.1068	0.1856	0.2399	1.2636
LBBB	Maximum	0.3536	0.8575	1.6794	3.2488	6.3775
	Minimum	-0.1061	-0.2575	-0.5957	-1.1763	-3.82
	Mean	0.0001	0.00003	0.0002	0.0001	-0.071
	Standard Deviation	0.0403	0.0761	0.1336	0.2194	0.6453
RBBB	Maximum	0.4384	1.1	2.6075	4.5738	4.4
	Minimum	-0.1838	-0.45	-0.9245	-1.91	-3.93
	Mean	3E-05	3E-06	0.0002	0.0017	-0.074
	Standard Deviation	0.0496	0.0932	0.1585	0.2667	1.3505
PVC	Maximum	0.4525	1.28	3.4595	5.9175	8.695
	Minimum	-0.1768	-0.51	-1.1561	-2.47	-3.144
	Mean	0.0001	0.0002	1E-05	0.0023	-0.055
	Standard Deviation	0.0844	0.1623	0.286	0.3932	1.4299
APB	Maximum	0.4525	1.28	3.2474	4.6213	1.9363
	Minimum	-0.1414	-0.265	-0.6081	-1.1038	-2.389
	Mean	3E-05	-0.00001	0.0005	0.0014	-0.08
	Standard Deviation	0.0675	0.1279	0.2211	0.2561	0.8259

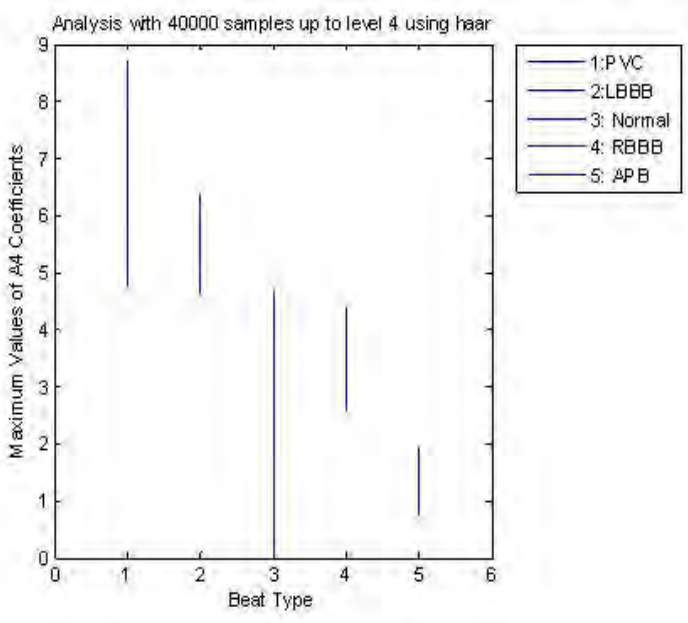


Figure 4.20: Range of values for different beat types obtained from the analysis with haar

4.7 Analysis Using coif2

Similarly selecting coif2 as the mother wavelet and performing an analysis up to level 4 with 40000 samples, the following complete results have been obtained:

Table 4.10: A complete set of result obtained from the analysis with coif2

ECG Beat Type	Extracted Features	Subbands				
	(Highest Values)	D1	D2	D3	D4	A4
Normal	Maximum	0.1156	0.6579	2.4581	4.0064	4.9486
	Minimum	-0.0264	-0.1661	-0.5599	-2.3725	-4.604
	Mean	1E-05	3E-05	0.0003	0.0001	-0.078
	Standard Deviation	0.0079	0.0418	0.1716	0.2722	1.2764
LBBB	Maximum	0.1222	0.6512	1.0747	1.9627	6.8667
	Minimum	-0.0267	-0.1248	-0.4662	-1.5527	-3.943
	Mean	0.0001	0.0001	0.0001	0.0004	-0.072
	Standard Deviation	0.0098	0.0344	0.0804	0.1762	0.6744
RBBB	Maximum	0.1878	0.7336	1.6256	2.7638	4.6058
	Minimum	-0.0296	-0.1708	-0.8253	-3.3921	-4.184
	Mean	4E-05	4E-05	2E-05	0.0013	-0.075
	Standard Deviation	0.0092	0.0442	0.1394	0.2169	1.3683
PVC	Maximum	0.2795	0.8384	2.654	4.3266	9.4153
	Minimum	-0.0391	-0.2762	-1.3345	-3.2814	-3.18
	Mean	0.0001	2E-05	0.0003	0.0033	-0.056
	Standard Deviation	0.0151	0.0531	0.2187	0.3991	1.4506
APB	Maximum	0.2332	0.7423	2.6027	3.5693	1.9981
	Minimum	-0.0379	-0.1937	-0.9505	-1.7396	-2.256
	Mean	3E-05	5E-05	0.0002	5E-05	-0.08
	Standard Deviation	0.0118	0.0546	0.1943	0.2864	0.835

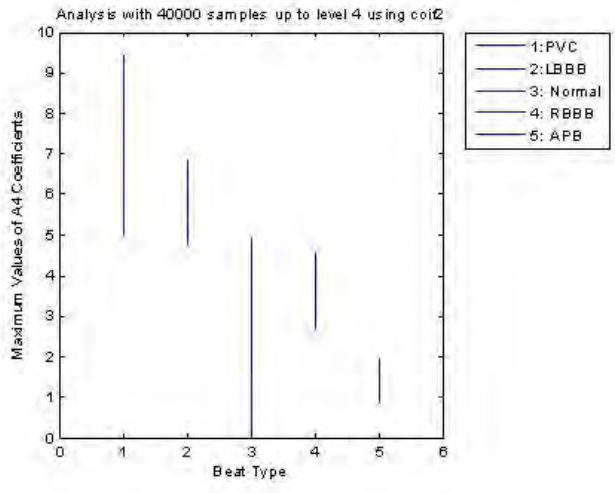


Figure 4.21: Range of the values for different beat types obtained with coif2 Analysis

4.8 Analysis Using sym4

Selecting sym4 as the mother wavelet and performing an analysis up to level 4 with 40000 samples, the following complete results have been obtained:

Table 4.11: A complete set of result obtained from the analysis with sym4

ECG Beat Type	Extracted Features	Subbands				
	(Highest Values)	D1	D2	D3	D4	A4
Normal	Maximum	0.1208	0.6538	2.7802	4.3621	5.4141
	Minimum	-0.0272	-0.1953	-0.5347	-2.1016	-4.687
	Mean	1E-05	4E-05	0.0001	-4E-05	-0.078
	Standard Deviation	0.0081	0.0434	0.1757	0.2782	1.2761
LBBB	Maximum	0.1385	0.7271	1.0383	2.2566	6.7812
	Minimum	-0.0269	-0.1429	-0.4887	-1.4737	-3.942
	Mean	0.0001	0.0001	0.0001	0.0001	-0.071
	Standard Deviation	0.01	0.0345	0.0819	0.1765	0.6737
RBBB	Maximum	0.216	0.5655	1.7536	3.0059	4.5205
	Minimum	-0.0305	-0.1758	-0.9315	-3.286	-4.122
	Mean	3E-05	3E-05	0.0005	0.0018	-0.074
	Standard Deviation	0.0095	0.0453	0.1344	0.2114	1.3694
PVC	Maximum	0.2823	0.8148	2.6066	4.7899	9.1898
	Minimum	-0.039	-0.2781	-1.2917	-3.0092	-3.244
	Mean	7E-05	1E-05	1E-05	0.0025	-0.055
	Standard Deviation	0.0153	0.0545	0.2163	0.4103	1.4479
APB	Maximum	0.2349	0.7329	2.6693	3.9327	1.9048
	Minimum	-0.0412	-0.2205	-0.8187	-1.6845	-2.202
	Mean	3E-05	6E-05	0.0004	0.0017	-0.08
	Standard Deviation	0.0121	0.0557	0.2078	0.274	0.8351

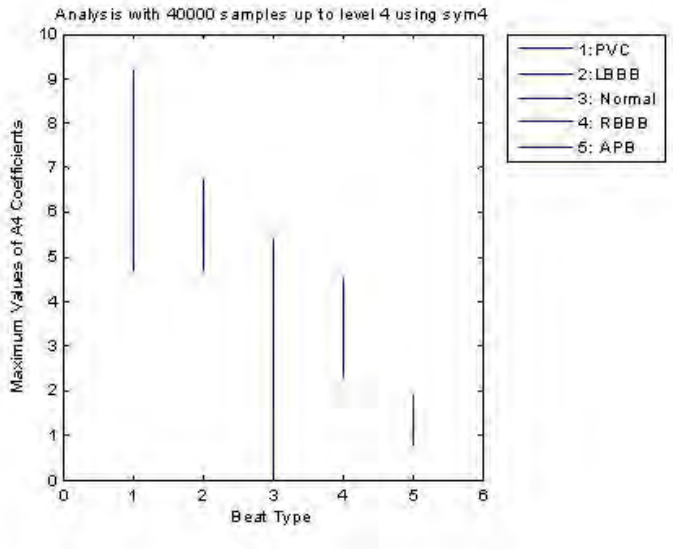


Figure 4.22: Range of the values for different beat types obtained with sym4 analysis

4.9 Analysis Using db10

Selecting db10 as the mother wavelet and performing an analysis up to level 4 with 40000 samples, the following complete results have been obtained:

Table 4.12: Complete set of result obtained from the analysis with db10

ECG Beat Type	Extracted Features	Subbands				
	(Highest Values)	D1	D2	D3	D4	A4
Normal	Maximum	0.092	0.3414	2.0578	3.5655	4.6675
	Minimum	-0.0271	-0.1379	-0.6513	-1.778	-5.2413
	Mean	1E-05	0.0001	0.0001	2E-05	-0.0784
	Standard Deviation	0.0069	0.0239	0.1703	0.2728	1.2774
LBBB	Maximum	0.0972	0.7938	0.9149	2.3684	6.2197
	Minimum	-0.0246	-0.0857	-0.2918	-1.0249	-3.8184
	Mean	0.0001	4E-05	0.0001	0.0003	-0.0719
	Standard Deviation	0.0074	0.0316	0.0735	0.1747	0.6798
RBBB	Maximum	0.0701	0.5409	1.9349	2.6897	4.1979
	Minimum	-0.0224	-0.1173	-0.9162	-2.0854	-3.2977
	Mean	4E-05	3E-05	0.0004	0.0018	-0.0751
	Standard Deviation	0.0069	0.0344	0.1371	0.2168	1.3701
PVC	Maximum	0.1307	0.4111	2.1333	4.8651	10.075
	Minimum	-0.0299	-0.1657	-1.1065	-2.3627	-3.2915
	Mean	7E-05	8E-05	1E-05	0.0018	-0.0556
	Standard Deviation	0.0139	0.0384	0.2027	0.4195	1.4513
APB	Maximum	0.1048	0.4223	2.43	3.5007	1.3933
	Minimum	-0.0361	-0.1567	-0.8072	-1.2219	-2.2489
	Mean	4E-05	4E-05	0.0004	0.0006	-0.0801
	Standard Deviation	0.0103	0.0361	0.1954	0.2891	0.8349

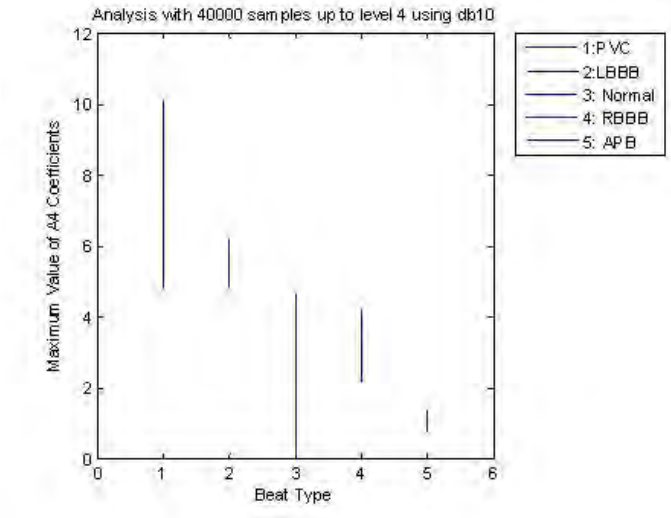


Figure 4.23: Range of the values for different beat types obtained with db10 analysis

4.10 Analysis Using bior6.8

Selecting bior6.8 as the mother wavelet and performing an analysis up to level 4 with 40000 samples, the following complete results have been obtained:

Table 4.13: A complete set of result obtained from the analysis with bior6.8

ECG Beat Type	Extracted Features	Subbands				
	(Highest Values)	D1	D2	D3	D4	A4
Normal	Maximum	0.0935	0.4197	2.4478	3.9898	4.7549
	Minimum	-0.0248	-0.1685	-0.5511	-2.3106	-4.9213
	Mean	1E-05	0.00004	0.0003	0.0001	-0.0781
	Standard Deviation	0.0069	0.0254	0.1575	0.2745	1.2834
LBBB	Maximum	0.0737	0.5968	1.4037	2.0982	6.8321
	Minimum	-0.0229	-0.1001	-0.3995	-1.4862	-3.8678
	Mean	0.0001	0.00005	0.0004	0.0004	-0.0717
	Standard Deviation	0.0075	0.0297	0.0739	0.1689	0.6909
RBBB	Maximum	0.1247	0.7056	1.5592	2.6078	4.7498
	Minimum	-0.0211	-0.1271	-0.7908	-3.2181	-4.4738
	Mean	4E-05	0.00002	-4E-05	0.0005	-0.0749
	Standard Deviation	0.0069	0.0328	0.1302	0.2072	1.3757
PVC	Maximum	0.2241	0.6251	2.4155	4.7243	10.113
	Minimum	-0.0352	-0.1744	-1.1546	-2.9575	-3.1859
	Mean	7E-05	0.0001	0.0003	0.0041	-0.0556
	Standard Deviation	0.0126	0.042	0.1864	0.4102	1.4648
APB	Maximum	0.1821	0.5762	2.427	3.8439	2.138
	Minimum	-0.0371	-0.1622	-0.7804	-1.7562	-2.5054
	Mean	4E-05	-4E-05	0.0003	-7E-05	-0.0803
	Standard Deviation	0.0095	0.0388	0.1828	0.2984	0.8413

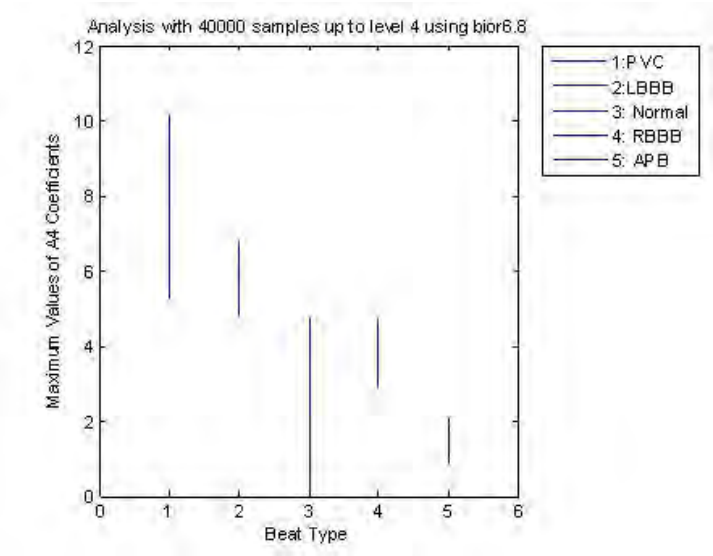


Figure 4.24: Range of the values for different beat types obtained with bior6.8 analysis

4.11 Discussion

The summary for different range of maximum values for wavelet co-efficient in A4 is given below.

Table 4.14: Range of the values of A4 (max) for different mother wavelets

Beat Type	**Range of Maximum Values of the Coefficients in A4**				
	haar	**coif2**	**sym4**	**db10**	**bior6.8**
Normal	0 to 4.6912	0 to 4.9486	0 to 5.4141	0 to 4.6675	0 to 4.7549
LBBB	4.6075 to	6.8667 to	4.6919 to	4.8218 to	4.8150 to
RBBB	2.555 to 4.4	2.7186 to	2.3354 to	2.2088 to	2.9086 to
PVC	4.7275 to	4.9854 to	9.189 to	4.7509 to	5.2518 to
APB	0.7513 to	1.9981 to	0.7890 to	0.7426 to	0.8524 to

Table 4.15: Properties of different mother wavelet functions used in the study

Property	**haar**	**coif2**	**sym4**	**db10**	**bior 6.8**
Arbitrary regularity	No	Yes	Yes	Yes	Yes
Compactly supported orthogonal	Yes	Yes	Yes	Yes	No
Compactly supported biothogonal	Yes	No	No	No	Yes
Symmetry	Yes	No	No	No	Yes
Asymmetry	No	No	No	Yes	No
Near symmetry	No	Yes	Yes	No	No
Arbitrary number of vanishing moments	No	Yes	Yes	Yes	Yes
Vanishing moments for ψ	No	No	No	Yes	No
Existence of ψ	Yes	Yes	Yes	Yes	Yes
Orthogonal analysis	Yes	Yes	Yes	Yes	Yes
Biorthogonal analysis	Yes	Yes	Yes	Yes	Yes
Exact reconstruction	Yes	Yes	Yes	Yes	Yes
FIR filters	Yes	Yes	Yes	Ye	Yes
Continuous transform	Yes	Yes	Yes	Yes	Yes
Discrete transform	Yes	Yes	Yes	Yes	Yes
Fast algorithm	Yes	Yes	Yes	Yes	Yes
Explicit expression	Yes	Yes	Yes	Yes	Yes

One of the objectives of our analysis was to select a mother wavelet function that shows the best performance in differentiating five particular types of cardiac phenomena. From the above results that we have obtained provide indication to conclude that among the five types of mother wavelets that have been considered here, db10 has provided the best performance.

To find a reason for such outcome, let us consider the chart of Table 4.15. A unique property of db10 wavelet function is asymmetry. ECG signals are non-stationary, rapidly varying signals which can hardly be confined within any particular shape or nature. The characteristic of the signal varies greatly from person to person even for same type of cardiac phenomenon. So for the analysis of such signals, asymmetric wavelet functions should be more effective than symmetric ones. That is what we have obtained from our study. A comparative statistical values for different cardiac phenomena with db10 wavelet is shown in Table 4.16.

Table 4.16: Comparison of statistical values for different cardiac phenomena

ECG Beat Type	**No. of Records Considered in the Study**	**A4(max)**			
		Maximum	**Minimum**	**Mean**	**Standard Deviation**
Normal	4	4.6675	0	2.621	2.0053
LBBB	4	6.2197	4.8218	5.583	0.5918
RBBB	4	4.1979	2.2088	3.207	0.8171
PVC	4	10.0746	4.7509	7.809	2.4694
APB	3	1.3933	0.7425	1.155	0.3587

The main objective of our analysis was to develop a possible algorithm for differentiating five types of cardiac phenomena. Based on the maximum values of approximation coefficients up to level 4 for discrete wavelet transform (DWT) of the sample signals, we can select db10 as the most appropriate mother wavelet function to fulfill this task.

However by observing the results obtained for db10 from table 5.9 and figure 5.4, we can conclude that the target of differentiating all of the five ECG beats has been achieved partially, not fully. Based on our approach, it has been possible to:

- Differentiate PVC from Normal beat, RBBB and APB.
- Differentiate LBBB from Normal beat, RBBB and APB
- Differentiate normal ECG beat from LBBB & PVC.
- Differentiate RBBB from PVC, LBBB and APB.
- Differentiate APB from PVC, LBBB and RBBB.

Chapter 5
CONCLUSION

5.1 Conclusion

The technology of the electrocardiogram, which is over 100 years old, can still be used to discover new clinical entities in cardiology. In this thesis, we have tried to develop a method for differentiating some particular ECG beats using discrete wavelet coefficients. The experimental results of this analysis have been presented and based on these results a possible algorithm has been developed. Also a comparison has been made between the performances of different mother wavelet functions. As an outcome of this analysis, we have found that asymmetric mother wavelet functions can be more effective than symmetric ones for the analysis of signals with random characteristics like the ECG signal. In our experiment we used five mother wavelet functions: haar, coif2, sym4, bior6.8, db10. Among them db10, which is the only one possessing asymmetric property, has provided the most optimum result.

Our proposed algorithm does have some limitations. Firstly, a major goal of this thesis was to differentiate some cardiac phenomena by directly applying signal processing techniques. The method that we have used has succeeded to achieve this target partially, not fully. Secondly, for the analysis we have used a fixed number of samples (40000 samples) of ECG signals. A variation in the number of samples can cause change in the results. So this can be considered as a limitation of this method. Finally, for our work we have considered five particular cardiac phenomena and used some particular records of the MIT-BIH database. To make this method universally applicable, study need to be carried out with a broad range of data covering all possible types of cardiac phenomena.

5.2 Future Perspective

A major characteristic of the methodology that we have used is its simplicity. The method that we implemented is a simple and straightforward one. Based on the maximum values approximation coefficients by performing discrete wavelet transform up to level 4, a decision has been made. A straightforward method like this one may not always provide

the best result. But it is free from complexity, easily understandable, requires less computational time and power. By overcoming the limitations of our proposed algorithm, this method can be further improved and can be made more effective for diagnosis of cardiac diseases. Further analysis with more number of symmetric and asymmetric wavelet functions should be carried out to generalize the findings of this study and to detect other types of cardiac abnormalities.

REFERENCES

1. M. Stout, “Athletes’ heart and echocardiography”, *Journal of Cardiovascular Ultrasound & Allied Techniques*, vol. 25, no. 7, pp. 749-754, Blackwell Publishing , August 2008.
2. K. Chang, C. Wen and M. Yeh, “Grey relational algorithm for ECG signal pattern recognition”, *Proceedings of the IEEE International Conference on Networking, Sensing and Control*, vol. 2, pp. 725-730, 2004.
3. E. D. Ubeyli, “Analysis of ECG signals by diverse and composite features”, *Journal of Electrical & Electronics Engineering*, vol.7, no. 2 , pp. 393 – 402, 2007.
4. E. M. Tamil, N.H. Kamaruddin , R. Salleh, M.Y. I. Idris, N. M. Noor and A, M. Tamil , “Heartbeat electrocardiogram signal feature extraction using discrete wavelet transforms” .
5. C. Li, C. Zheng and C. Tai, “ Detection of ECG characteristic points using wavelet transforms”**,** *IEEE Trans on Biomedical Engineering*, vol. 42, pp. 21-28, 1995.
6. M. A. Khayer and M. A. Haque, “ECG peak detection using wavelet transform”, *Proceedings of the 3rd International Conference on Electrical and Computer Engineering, (ICECE 2004)*, pp. 518-521, December 2004.
7. C. Torrence and G. P. Compo, “A practical guide to wavelet analysis”, *Bulletin of the American Meteorological Society*, vol. 79, no. 1, pp. 61–78.
8. G.M. Patil, K. S. Rao and K. Satyanarayana, “Heart disease classification using discrete wavelet transform coefficients of isolated beats”, *Proceedings of the 13th International Conference on Biomedical Engineering*, vol. 23, pp.60-64, 2008.
9. P.S. Addison, J.N. Watson, G.R. Clegg, M. Holzer, F. Sterz and C.E. Robertson, “Evaluating arrhythmias in ECG signal using wavelet transform”, *IEEE Engineering in Medicine and Biology Magazine*, vol. 19, pp.104 – 109.
10. W. Chen, Z, Mo, W. Guo, “Detection of QRS complexes using wavelet transforms and golden section search”, *Proceedings of International Conference on Intelligent Systems and Knowledge Engineering (ISKE 2007)*, October 2007.

11. A. Moulton, “Metronomic hardware design used to maintain respiratory tempo during EKG signal acquisition”, *Proceedings of the IEEE 31st Annual Northeast Bioengineering Conference*, pp 281- 282, 2005.
12. G. Cornelia and R. Romulus, “ECG signals processing using wavelets”.
13. S. S. Ilic, “Detection of the left bundle branch block in continuous wavelet transform of ECG signal”.
14. K. Anant, F. Dowla and G. Rodrigue, “Vector quantization of ECG wavelet coefficients”, *IEEE Signal Processing Letters*, vol. 2, no. 7, July 1995.
15. P.S. Hamilton and W.J. Tompkins, “Quantitative investigation of QRS detection rules using the MIT/BIH arrhythmia database”, *IEEE Trans on Biomedical Engineering*, vol. 33, no.12, December 1986.
16. J. Henriques, M. Brito, P. Gil, P. Carvalho, “Searching for similarities in nearly periodic signals with application to ECG data compression”, *Proceedings of the 18th International Conference on Pattern Recognition*, vol. 3, pp 942 - 945, 2006.
17. MIT-BIH Arrhythmia Database: www.physionet.org
18. www.ecglibrary.com
19. www.ecgpedia.org
20. www.mathworks.com