A Dissertation On

ECG Denoising Using The Wavelets And Robust Analysis Of ECG Signals

Submitted In Partial Fulfillment Of The Requirement

For The Award Of Degree Of

Master of Technology

In

Signal Processing and Digital Design

Submitted By

NAVEEN KUMAR MUNJAL

Roll No. 2K11/SPD/09

Under The Esteemed Guidance Of

M.S. CHAUDHARY

(Associate Professor)

Department of Electronics and Communication Engineering

DELHI TECHNOLOGICAL UNIVERSITY

2011-2013

DECLARATION BY THE CANDIDATE

July 2013

I hereby declare that the work presented in this dissertation entitled **"ECG Denoising using wavelets and Robust Analysis Of ECG Signals"** has been carried out by me under the guidance of **Mr. M.S. Chaudhary**, Associate Professor, Department of Electronics & Communication Engineering, Delhi Technological University, Delhi and hereby submitted for the partial fulfillment for the award of degree of Master of Technology in Signal Processing & Digital Design at Electronics & Communication Department, Delhi Technological University, Delhi.

I further undertake that the work embodied in this major project has not been submitted for the award of any other degree the best of my knowledge.

NAVEEN KUMAR MUNJAL

M.Tech. (Signal Processing & Digital Design)

Roll No. 2K11/SPD/09

Department of Electronics & Communication Engineering

Delhi Technological University, New-Delhi-110042

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CERTIFICATE

This is to certify that the work contained in this dissertation entitled "**ECG Denoising using wavelets and Robust Analysis Of ECG Signals** "submitted in the partial fulfillment, for the award for the degree of M.Tech in Signal Processing and Digital Design at **DELHI TECHNOLOGICAL UNIVERSITY** by **NAVEEN KUMAR MUNJAL, ROLL NO. 2K11/SPD/09** is carried out by her under my supervision. The matter embodied in this project work has not been submitted earlier for the award of any degree or diploma in any university/institution to the best of my knowledge and belief.

Date: _____

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(M.S. Chaudhary)

Associate Professor

Project Guide

Department of Electronics and Communication Engineering

Delhi Technological University, New-Delhi-110042

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ACKNOWLEDGEMENT

It is a great pleasure to have the opportunity to extend my heartfelt gratitude to everybody who helped me throughout this thesis.

First of all, I thank **my parents** who made me capable of taking up this thesis. They have always motivated and blessed me for all my endeavors.

It is a distinct pleasure to express my deep sense of gratitude and indebtedness to **Dr. Rajiv Kapoor,** HOD, Department of Electronics Engineering, (DTU), and Assoc. Professor **M. S. Chaudhary** for his invaluable guidance, encouragement and patient review. It was indeed a privilege and honor to work under his supervision.

Special thanks to Chandradeep Singh, Researcher, (Department Of Electrical Engg, Indian Institute Of Technology, Bombay) for devoting his time and helping me whenever i needed his guidance.

I convey the thanks to all the staff members of Department of Electronics and Communication Engineering, DELHI TECHNOLOGICAL UNIVERSITY for the help rendered in fulfilling this project.

I take this opportunity to appreciate all my **friends** at DTU, in particular for their constant unconditional support, help and making this work duration jovial.

Above all, we are grateful to **God** for being with us and showing us the right path.

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NAVEEN KUMAR MUNJAL

M.Tech. (Signal Processing & Digital Design)

Roll No. 2K11/SPD/09

Department of Electronics & Communication Engineering

Delhi Technological University, New-Delhi-110042

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I dedicate this thesis

To my parents {bauji, mom}, my teachers and my friends for

Supporting me all the way since the beginning of my studies & doing all the

Wonderful things for me.

And

also dedicated to my sister Rita arora who has been a great source of motivation and inspiration.

List Of Figure

ABSTRACT

The project aims at the successful development of an algorithm to rapidly and efficiently denoising the ECG waveforms . In general, ECG signals affected by noises such as baseline wandering,power line interference, electromagnetic interference, and high frequency noises during data acquisition. In order to retain the ECG signal morphology, several researches have adopted using different preprocessing methods. I have considered the Discrete Wavelet Transform (DWT) based wavelet denoising have incorporated using different thresholding techniques to remove three major sources of noises from the acquired ECG signals namely, power line interference, baseline wandering, and high frequency noises. seven wavelet functions ("db1","coif1","rbio1.1","dmey","bior1.1","haar" and "sym1") and four different thresholding levels are used to de-noise the noise in ECG signals.The proposed algorithm in this thsis can be used for accurate and fast feature extraction from any ECG signal and for further classification into normal and abnormal signal. Our work basically includes three phases namely de-noising of the input signal, detection of peaks and finally detecting the abnormality if any present.

Keywords: Electrocardiogram, Discrete Wavelet Transform(DWT), Feature Extraction, Classification, MIT-BIH Arrhythmia Database.

Chapter 1
Introduction

The electrocardiogram (or ECG) is a non-invasive signal that measures the electrical activity of the heart. By examining the ECG signal in detail, it is possible to derive a number of informative measurements from the characteristic ECG waveform. In the context of cardiac safety, these measurements take the form of a series of timing intervals within each individual heartbeat. Drug-induced changes in the ECG intervals are now the gold standard for assessing the potential of a drug to cause sudden cardiac death.

At the present time, ECG interval measurements for clinical trials are carried out manually by human expert analysts. This procedure is both costly and labour intensive. Furthermore, manual ECG interval measurements are susceptible to occasional mistakes by the analysts. These drawbacks typically limit the total number of electrocardiograms which can be success- fully analysed in a given trial. Automated methods for ECG interval analysis therefore offer the potential for a more extensive evaluation of ECG data from clinical trials, and hence a more robust assessment of drug safety.

Despite the advantages offered by automated approaches to ECG interval analysis, current automated systems are not sufficiently reliable to be used for the assessment of ECG data from clinical trials. The algorithms which underlie these systems typically make use of rule-based approaches (such as thresholding methods) in their analysis of the ECG signal. As a result, these algorithms often produce highly unreliable automated ECG interval measurements when the ECG signal is affected by noise, or exhibits unusual waveform morphologies.

The aim of this thesis is to develop an algorithm for automatically computing ECG interval measurements and an associated confidence measure in each of the automated measurements. The approach taken to this problem is to build a probabilistic model of the normal ECG waveform. The resulting model defines a probability density function over these types of ECG waveforms. This can then be used to derive both automated interval measurements and the associated confidence values from a given ECG signal.

1.1. Heart Contraction and Blood Flow:-

The heart is located under the ribcage in the center of chest between the right and left lungs [3]. The average adult heart is about the size of a clenched fist and weighs about 11 ounces (310 grams). It can beat more than hundred thousand times a day, pumping about two thousand gallons of blood through a sixty thousand mile network of vessels in the body. Figure 1.1 is a picture of the inside of a normal, healthy human heart.
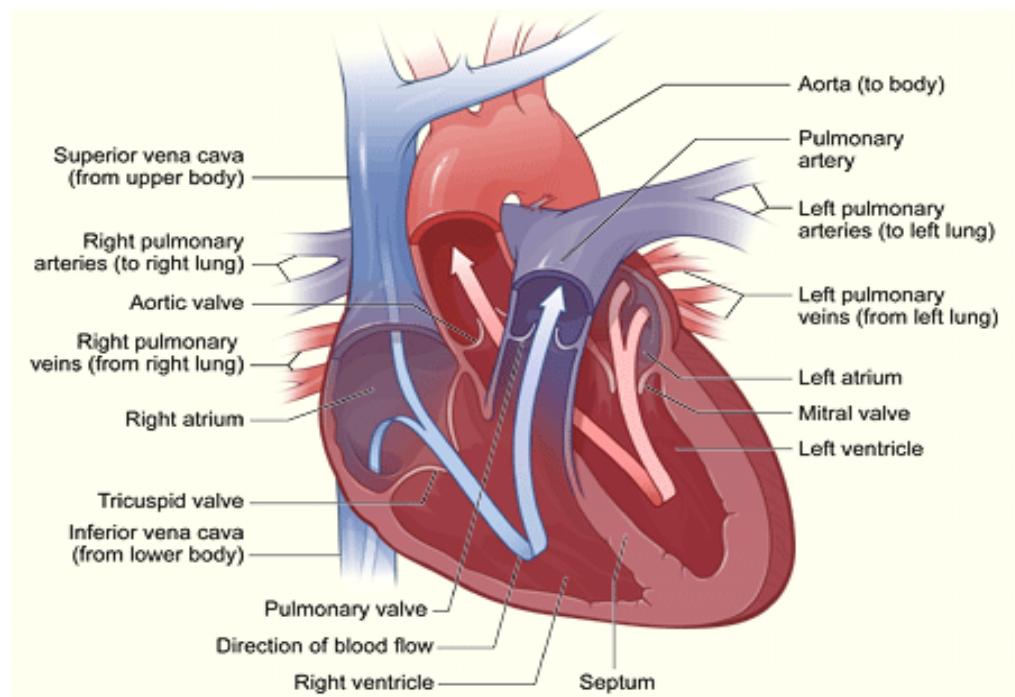
Figure 1.1 Heart Interior [4]

Figure 1.1 shows a cross-section of a healthy heart and its inside structures. The heart is divided into a right and a left side separated by a septum. Inside the heart there are four chambers; right atrium and ventricle, and left atrium and ventricle. These are separated by one-way gateways called valves. A pumping cycle begins when blood flows into the two upper chambers, called the atria.Oxygen-free blood from the body flows into the right atrium through the superior and inferior vena cava, while oxygen-rich blood from the lungs flows into the left atrium through the pulmonary veins. When the right atrium is filled with blood, it contracts and the tricuspid valve opens forcing blood into the right ventricle. At

the same time, the left atrium contracts and the mitral valve opens, then blood is pumped into the left ventricle. After this takes place the tricuspid valve and the mitral valve are closed to prevent blood from flowing back into the right and left atria. Filled with blood, the ventricles contract, the left ventricle contracting an instant before the right ventricle. When the left ventricle starts to contract, the aortic valve between the left ventricle and the aorta opens and that contraction is what pumps oxygen-rich blood into the rest of the body through the aorta. At the same time the right ventricle contracts and the pulmonary valve opens to let the blood pump into the lungs through the pulmonary artery then the pulmonary valve quickly closes to prevent blood from returning to the right ventricle. This cycle repeats over and over [5,6].

1.2. Electrical Conduction System of the Heart:-

The contraction of the heart is initiated and coordinated by an electrical signal produced by a Sinoatrial Node, known as the SA node. Its cluster of special muscle cells located on the wall of the right atrium is shown in Figure 1.2. When the right atrium is filled with blood, the electrical signal - established as a result of "more negative ions inside the cell than outside" as Antranik (2012) writes in Physiology, Science - from the SA node spreads rapidly to both the right and left atria causing the atria to contract in smooth synchronicity[7,8].
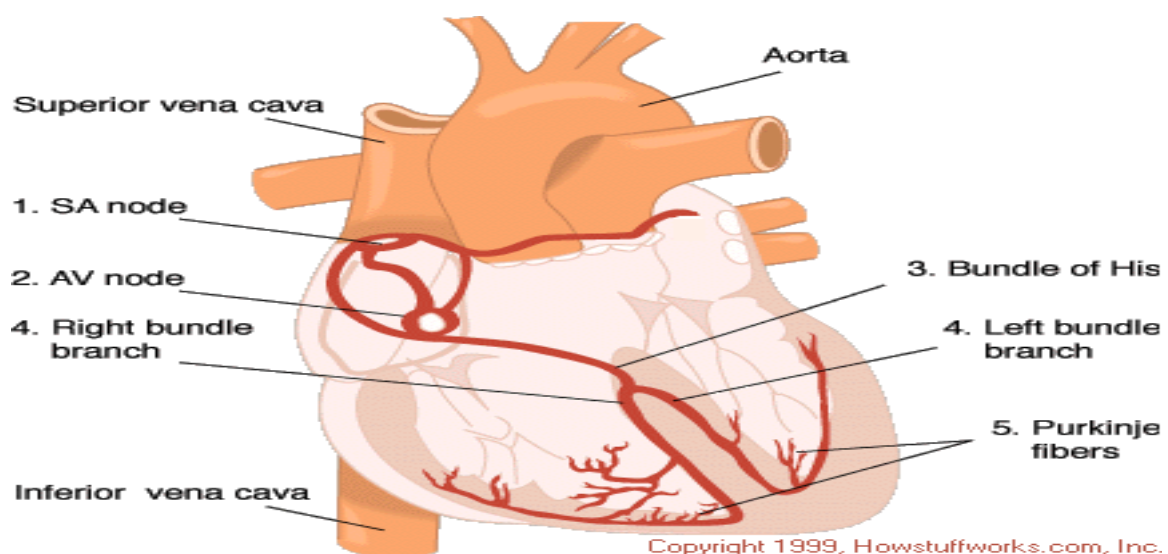
Figure 1.2 Conduction System of the Heart [9]

Figure 1.3 shows five waves; each of which is given a letter (P-Q-R-S-T) to distinguish one wave from the other. The P wave for instance, marks the contraction of the heart atria. The electrical impulse arrives at the atrio ventricular node (AV) located on the floor of the right atrium. At the AV node the impulse is delayed about 0.1 seconds after the contraction of the atria to allow the heart's right and left ventricles to fill with blood. On the ECG signal Figure 1-3, this interval is represented by the start of the line segments between the P and Q waves.The signal is released and is transferred to the Bundle of His which is "the part of the heart's electrical system that controls the beating of the cardiac muscle. It is made up of myocardial cells that contract when an electrical impulse passes through them, and also contains pacemaker cells that produce those electrical impulses" [10]. From the Bundle of His, the signal fibers are divided into left and right bundle branches on the ECG signal Figure 1.3 that is represented by the Q wave. The signal leaves the left and right bundle branches through the Purkinje fibers that connect directly to the cells in the walls of the heart ventricles. The signal spreads quickly across the cells of the ventricle walls and both ventricles contract, but not at exactly the same time. The left ventricle starts to contract an instant before the right ventricle, the R wave marks the contraction of left ventricle while the S wave marks the contraction of right ventricle.
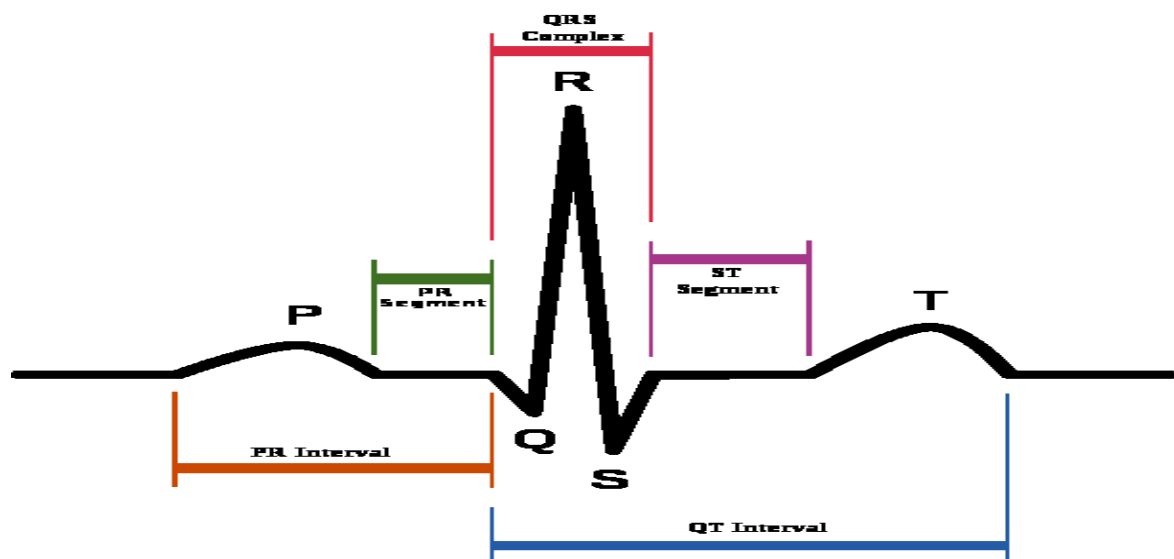
Figure 1.3 The Electrical ECG Signal [11]

Then the walls of the ventricle relax and await the next signal. On the ECG signal Figure 1.3, the T wave marks the moment at which the ventricles are relaxing.

1.3 History of The ECG signal:-

The technique of electrocardiography originated in the early part of the 20th century through the pioneering work of Augustus Waller and, independently, Willem Einthoven (Cooper, 1986). Einthoven, a Dutch doctor and physiologist, used a "string galvonometer" to register the electrical activity of the heart from the surface of the body. The resulting electrical signal was termed the electrocardiogram or ECG, and earned Einthoven the Nobel prize for medicine in 1924.

The importance of the ECG derives from the diagnostic information which can be obtained from a detailed analysis of the individual ECG waveforms produced as a result of each heartbeat. In particular, the ECG is essential for the identification of disorders of the cardiac rhythm, as well as for the diagnosis of abnormalities of the heart. In addition, the ECG can also provide a good indicator of the presence of generalised disorders that affect the rest of the body [18].

More recently, the ECG has become an essential tool for identifying drug-induced abnormalities of the cardiac rhythm. As a result, regulatory authorities throughout the world have established electrocardiographic guidelines for the safety screening of new drugs before they can be approved for clinical use. This in turn has led to a renewed interested in the analysis of the ECG, and a subsequent "renaissance in electrocardiography"[20].

1.4. ECG Lead Placements:-

The ECG is a measurement of the total electrical activity generated by the heart, measured by placing skin electrodes on the body surface at different locations and connecting these electrodes in different configurations to a voltage amplifier and recorder.

1.4.1. The Standard Leads (Bipolar):-

Bipolar leads are those that have one positive and one negative pole as shown in Figure 1.4. By attaching electrodes to the left arm, which is a positive pole and the right arm as a negative one designated as Lead I a potential difference between them is recorded. Another possible position is to attach the right arm as a negative pole and the left leg as a positive one; this is named as Lead II. When we attach the electrode to the left arm as a

negative pole and the left leg as a positive one, this makes lead III. Each of these leads measures the voltage between two points on the body.
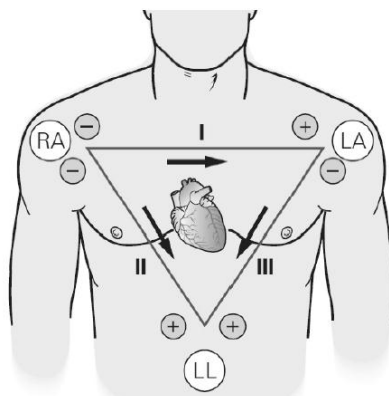
Figure 1.4 The Standard Leads (Bipolar) [12]

1.4.2. <u>The Augmented Leads (Unipolar):-</u>

Three additional limb leads can be obtained by recording a potential difference between an imaginary central neutral point based on two electrodes connected together to create an "average" electrode and finally connected through the ECG machine to the remaining electrode, as shown in Figure 1.5. These Leads are aVR, aVL, & aVF.
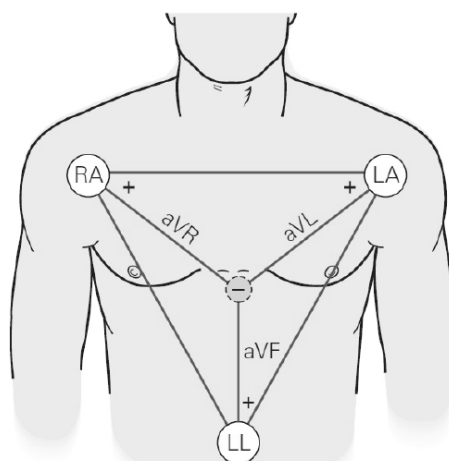
Figure 1.5 The Augmented Leads (Unipolar) [12]

1.4.3. <u>The Chest Leads (Unipolar):-</u>

In addition to the three standard limb leads and the three augmented limb leads, there are six leads labeled as "V" leads, noted as V1 to V6 as shown in Figure 1.6.This configuration places

six positive electrodes at specific positions on the rib cage.
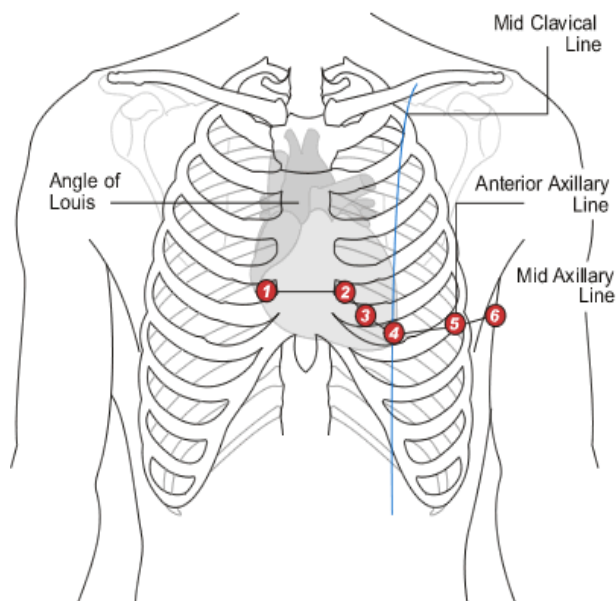
Figure 1.6 The Chest Leads (Unipolar) [13]

1.5. <u>The 10-second 12-lead ECG:-</u>

The basis of standard clinical electrocardiography is the 10-second 12-lead ECG. This type of ECG recording makes use of four limb electrodes and six chest electrodes in order to provide a comprehensive picture of the electrical activity of the heart from 12 different "viewpoints" around the surface of the body. Figure 1.1 overleaf shows the orientation of the electrical axis of the standard 12 leads in relationship to the body surface.

It is important to recognise that the term "lead" does not refer to the actual wires that connect the subject to the ECG recorder, but rather to the signals which results from the potential differences measured between the different pairs of electrodes. Since the individual electrodes are strategically positioned on the chest and the limbs, each lead effectively provides
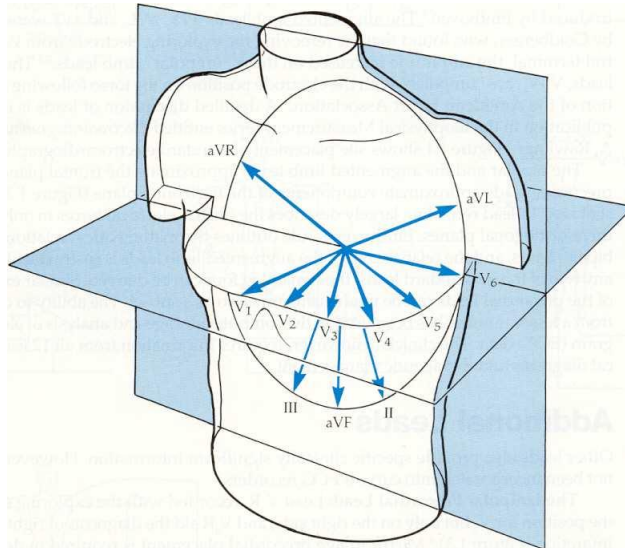
Figure 1.7: The orientation of the electrical axis of the standard 12 leads in relationship to the body surface.

a unique viewpoint of the heart's electrical activity. The standard 10-second 12-lead ECG records simultaneously the electrical activity mea- sured by the 12 different leads for a period of 10 seconds. Potential differences between the limb electrodes are used by the ECG instrumentation to generate six limb leads, and similarly potential differences between the chest electrodes are used to generate six chest leads. The individual leads which make up the 12-lead ECG are referred to as follows:

- Limb leads: I, II, III, aVR, aVL, aVF

- Chest leads: V1, V2, V3, V4, V5, V6

The particular viewpoint which each lead has of the heart determines the characteristic form of the corresponding ECG signal. For example, if electrical current is flowing towards a given lead then the corresponding ECG signal will exhibit an upward (i.e. positive) deflection. Conversely, current flowing away from a lead will give rise to a downward (i.e. negative) deflection in the ECG signal. As a result, the morphology of the waves which make up the ECG signals for the different leads varies according to the particular lead chosen.

Figure 1.8 shows an example of a standard 10-second 12-lead ECG recording. The upper plot shows the 10-second ECG signal from lead II. The lower plot shows a single ECG waveform (i.e. heartbeat) from each of the 12 different leads. It is evident that the different ECG leads
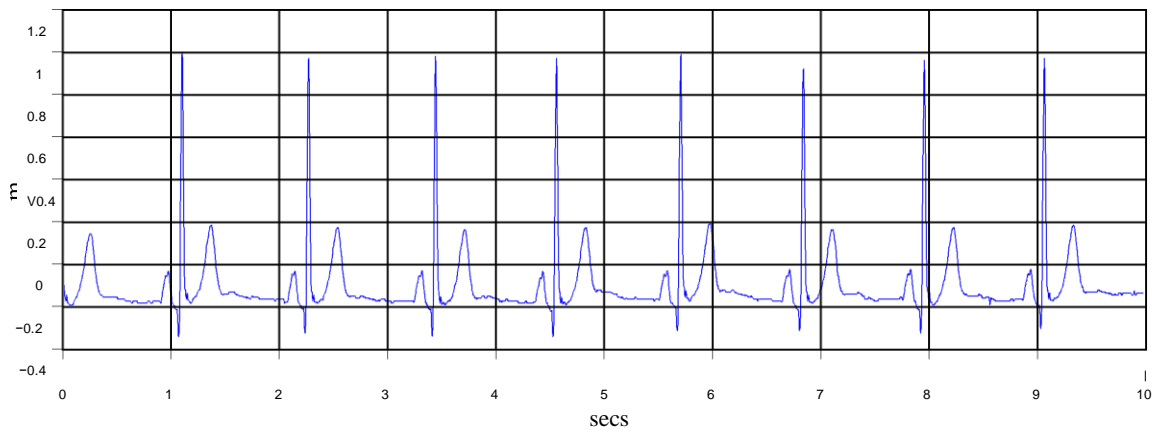
Figure 1.8(a) 10-second ECG signal from lead II
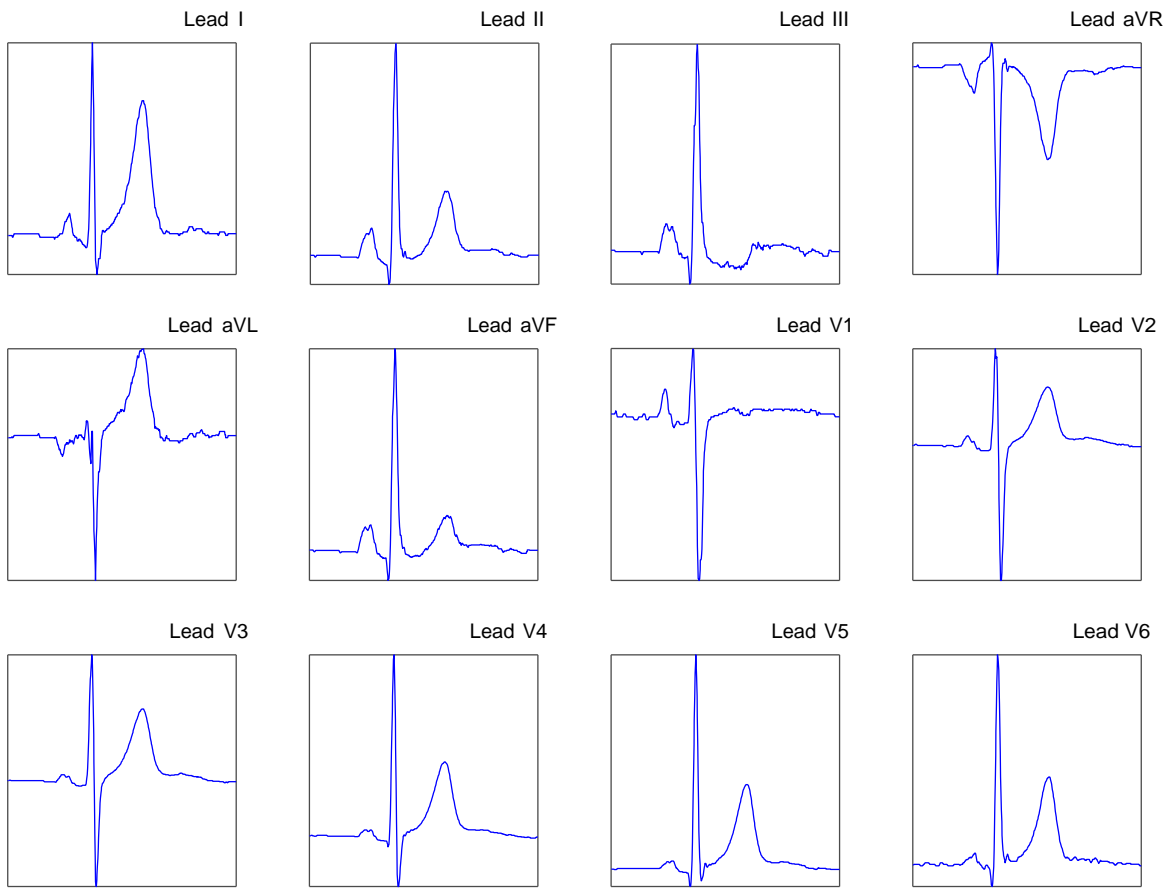
(b) Selected ECG waveforms from the 12 different leads

Figure 1.8: An example of a standard 10-second 12-lead ECG recording.

exhibit a variety of different waveform morphologies.Modern 12-lead ECG machines typically record the ECG signal at a sampling frequency of 500 Hz. This rate is considered sufficient to capture all the information in the ECG signal, and hence to enable the ECG to be used for the purposes of clinical diagnosis[2].

1.6. <u>The ECG waveform</u>:-

To understand the genesis of the ECG waveform, it is useful to consider first the basic anatomy and function of the heart. The heart is a four-chambered pump which provides the driving force for the circulation of the blood around the body. A wall divides the heart cavity to form a double-pump configuration. Each side of the heart is then further divided into an upper chamber known as the atrium, and a lower chamber known as the ventricle. The atria and the ventricles in the heart are composed of muscle cells (or "myocytes").

The rhythmic contractions of the heart stem from the flow of ions through channels in the membranes of the heart's muscle cells.The cell membrane is the dividing medium between the extracellular and the intracellular fluids, each of which has a different ionic concentration. When a cell is stimulated electrically, the permeabilities of the membrane to ionic transfer are modified.The resulting flow of ions through the cell membrane gives rise to an electrical signal known as an action potential.This in turn results in a mechanical contraction of the cell[1,2].

The propagation of action potentials through the atria and the ventricles during each heart-beat results in a set of distinct features in the characteristic ECG waveform. These features represent either depolarisation (electrical discharging) or repolarisation (electrical recharging) of the heart muscle cells in the atria and the ventricles.

Figure 1.4 shows a human ECG waveform and the associated features. The standard features of the ECG waveform are:

- The P wave
- The QRS complex
- The T wave

Additionally a small U wave (following the T wave) is occasionally present. The origin of

the U wave is uncertain; however it is believed that small U waves and large U waves have different physiological origins [14]. Typically U waves are less than one third the amplitude of the preceding T wave, and possess the same polarity.

The cardiac cycle begins with the P wave, the start and end of which are referred to as P_{on} and P_{off} .The P wave corresponds to the period of atrial depolarisation in the heart. This is followed by the QRS complex, which is generally the most recognisable feature of an ECG
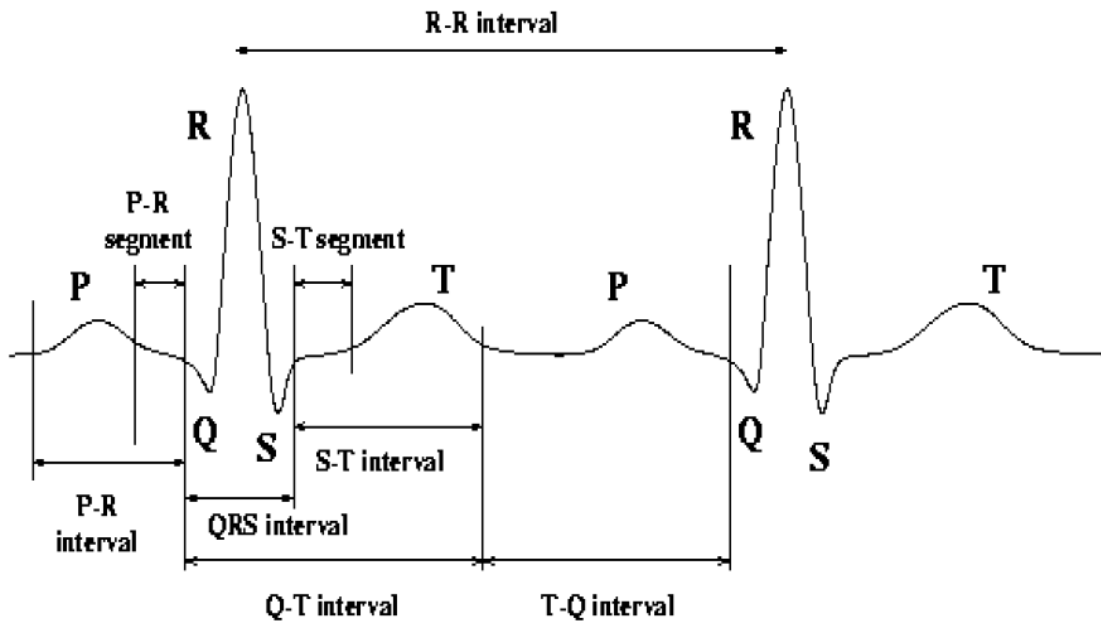
Figure 1.9: A typical human ECG waveform showing the characteristic ECG features.

waveform, and corresponds to the period of ventricular depolarisation. The start and end of the QRS complex are referred to as the Q and J points. The T wave follows the QRS complex and corresponds to the period of ventricular repolarisation. The end of the T wave is referred to as T_{off} and represents the end of the cardiac cycle (presuming the absence of a U wave).

The regions of the ECG waveform in-between the different features are referred to as the isoelectric baseline regions. This thesis uses the term "Baseline 1" to refer to the baseline between the end of the P wave and the start of the QRS complex (i.e. P_{off} to Q), and "Baseline2" for the baseline between the end of the T wave and the start of the P wave for

the following beat (i.e T_{off} to next P_{on}).

The morphology of the various ECG waveform features depends on a number of factors, including the particular ECG lead under consideration, as well as the presence of cardiovascular diseases or cardiac abnormalities in the given subject. The different classes of morphology for P waves and T waves include upright, inverted, and biphasic. The term "biphasic" is used to refer to a wave which consists of a negative deflection followed by a positive deflection, or vice versa. In addition to the the standard morphologies, P waves and T waves may also be flat, such that they are difficult to distinguish from the isoelectric baseline.

1.7. ECG interval analysis:-

The timing between the onset and offset of particular features of an ECG waveform is referred to as an interval. Measurements of the ECG intervals are of great importance since they provide an indirect measure of the state of the heart and can be indicative of the presence of certain cardiological conditions.

Figure 1.9 overleaf shows a typical ECG waveform and the three standard ECG intervals. These are known as the QT interval, the PR interval, and the QRS duration. We now consider each of these in turn.

1.7.1. QT interval:-

Perhaps the most important timing interval in the ECG waveform is the QT interval. The QT interval is defined as the time from the start of the QRS complex to the end of the T wave, i.e. $T_{off} - Q$. It corresponds to the total duration of electrical activity (both depolarisation and repolarisation) within the ventricles in a given heartbeat. It is important to recognise that the QT interval varies according to the particular ECG lead selected for analysis. Thus, the QT intervals measured from the same heartbeat on a number of different leads will typically have a range of different values [15].
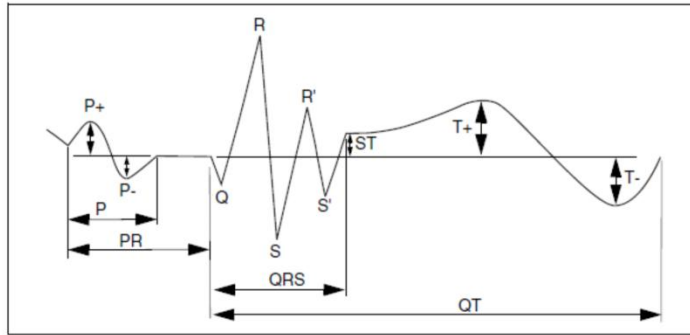
Figure 1.10: An ECG waveform showing together with the standard ECG intervals.

1.7.2. <u>**Long QT syndrome**</u>:-

Long QT syndrome (LQTS) refers to the condition whereby the QTc interval is prolonged with respect to its normal range of values. Table 1.1 shows the accepted ranges of normality for the corrected QT interval [16].

Long QT syndrome is an extremely serious condition that renders sufferers vulnerable to a very fast, abnormal heart rhythm (an "arrhythmia") known as torsade de pointes . Although This Heart Rhythm Is Itself Not Fatal, It Can In Some Circumstances Degenerate Into Ventricular Fibrillation, a Rapidly Fatal Arrhythmia. When this occurs the heart is unable to beat effectively and the blood flow to the brain falls dramatically. The resul is a sudden loss of consciousness quickly followed by cardiac death.

Long QT syndrome can be either inherited (the genetic form) or acquired. The inherited form is believed to be present in as many as 1 in 5000 people in the USA alone and may cause as many as 3000 deaths (mostly in children and young adults) each year [17]. The acquired form of LQTS generally results from the administration of certain drugs which lengthen the duration of ventricular repolarisation in each heartbeat. This issue, and its importance in the context of clinical drug trials.

1.7.3. <u>**PR interval**</u>:-

The PR interval is defined as the time from the start of the P wave to the start of the QRS complex, i.e. $Q - P_{on}$. It corresponds to the time from the onset of atrial depolarisation to

the onset of ventricular depolarisation.

The PR interval has precise time limits in health. In particular, it should be in the region of 0.12 to 0.2 seconds long. Drug-induced prolongation of the PR interval indicates that the drug slows atrioventricular conduction, which can in turn lead to "heart block" [18].

1.7.4. <u>QRS duration:-</u>

The QRS duration (QRS_d), i.e. J − Q, corresponds to the duration of ventricular depolarisation in each heartbeat. In health its value is normally no longer than 0.12 seconds. Drug-induced prolongation of the QRS duration indicates that the drug delays the time taken for conduction through the ventricles. This effect has the potential to cause arrhythmias.

1.8. <u>Heart Disease and ECG:-</u>

Heart disease is among the main causes of death in most countries of the world. According to the Statistics Canada [19], report titled "Leading Causes of Death", cancer and heart disease are the two leading causes of death in Canada; responsible for just over one-half (51%) of the 238,617 deaths in 2008. Heart disease, which comes second after cancer, caused 21% of all deaths in Canada in 2008. Therefore, it is important to have proper methods to determine the cardiac condition of a patient. Electrocardiography (ECG) is a tool that is widely used by cardiologists to measure the amount of electrical activity in the heart. This allows them to diagnose various types of heart disease, including heart failure, heart attacks and arrhythmia. Unfortunately, the ECG is often contaminated by noise that can be within the critical frequency band, which makes manual and automatic analysis difficult.

Traditionally, an experienced cardiologist would have performed visual ECG analysis in the time domain. Nowadays, cardiologists use a computerized analysis which can reduce their workload. This starts by converting the ECG continuous time signal into a discrete- time signal by taking samples of the continuous time signal at discrete instants. Cardiologists can then

use algorithms to enhance and interpret the ECG signal. The use of a computer provides clear physical information and storage of patients data.

In addition, there are various digital filters to remove the noise. In this chapter, we provide background information on heart contraction and the electrical conduction system of the heart and we present the scope of this thesis.After a deep research on the Wikipedia, a medical textbook, taking guidance from a doctor and reviewing some medical journals, a list of diseases was made that could be detected by an ECG signal. However, the interpretation of the ECG is only the initial step of detecting a disease and so, we cannot say for sure whether a disease is present in the patient just on the basis of the ECG reading. But, there are chances that a disease might be present in the patient. Hence, after listing down the diseases and the corresponding conditions that are sufficient to detect the disease, an algorithm was made for proper detection using the basic "if-else"statememt.

The following table consists of the diseases listed down along with the conditions that are sufficient to detect the diseases:

S.N.	Diseases	Conditions (s=seconds, mV=millivolts)
1.	Bundle Branch Block	QRS interval>0.12s
2.	Ventricular Tachycardia	RR interval<0.6s AND QRS interval>0.12s
3.	Long QT Syndrome	Q-T interval >0.57s
4.	Sinus Bradycardia	R-R interval >1s or P-P interval>1s
5.	Junctional rhythm	R-R or P-P >1s AND (inverted Pwave of flat P)
6.	Hypekalemia	Q-T interval <0.35s AND tall T(Tamp>0.4mV)
7.	Hypokalemia	Q-T interval>0.43s AND flat T(Tamp <0.05mV)
8.	Hypercalcemia	Q-T interval <0.35s
9.	Hypocalecemia	Q-T interval>0.43s
10.	First Degree Atrio Ventricular Block	P-R interval >0.20s
11.	Myocardial ischemia	Inverted T wave OR Tall wave OR flat T wave
12.	Right Atrial Enlargement	Pamp >0.25mV
13.	Left Atrial Enlargement	Pwidth<0.10s
14.	Tachycardia	P-P interval <0.6s OR R-R interval <0.6s
15.	Atrial Flutter	P-P or R-R interval <0.6s AND QRS interval <0.12s AND regular tachycardia AND visible P AND atrial rate > ventricular rate

16.	Atrial Tachcardia	P-P or R-R interval <0.6s AND QRS interval <0.12s AND regular tachycardia AND visible P AND atrial rate > ventricular rate
17.	Atrio Ventricular Nodal Reentrant Tachycardia	P-P or R-R interval <0.6s AND QRS interval <0.12s AND regular tachycardia AND visible P wave

Table 1.2 Conditions for detecting various heart diseases

Following the information in the above table, code was generated for detecting the mentioned diseases. If the conditions match in the input signal, the corresponding disease is detected. After having collected all the data required for detection of the diseases, we started making the step by step algorithms and writing the codes. The very first step was generating the input signal in MATLAB. For this, a code was used and it gave the input signal with noise as shown above in the given figure.

Chapter 2
ECG Noises and Abnormalities

2.1. ECG Noise Sources & Abnormalities:-

In common with many other biomedical signals, the ECG can be affected by unwanted noise sources [20]. Figure 1.3 overleaf shows examples of ECG signals affected by a variety of different noise sources, including:

1.Main interference : this results from capacitance effects between 50 (or 60) Hz power lines (e.g. in the walls, floor and ceiling) and the ECG recording equipment. This type of noise can generally be removed through the use of an appropriate notch filter[21].

2.Muscle artefact : this results from the contraction (i.e. tremor) of skeletal muscle under an ECG electrode. Unfortunately this source of noise has a similar bandwidth to that of the ECG and therefore cannot be removed by simple filtering techniques.

3.Electrode contact noise : this results from a poor contact between an ECG electrode and the skin (e.g. due to poor adhesive or absence of conducting gel between the electrode and the skin).

4.Movement artefact : this results from the movement of the subject (and hence one or more electrodes) during the ECG recording which gives rise to artefact (i.e. unwanted electrical potential changes) in the ECG signal.

An additional form of ECG abnormality is caused by the misplacement of the ECG electrodes (with respect to their standardised positions). This is particularly common with the limb leads where it is relatively easy to inadvertently swap the two arm electrodes [18]. This results in inversions of the ECG waveforms with respect to their normal morphologies and all the noises explained given below:
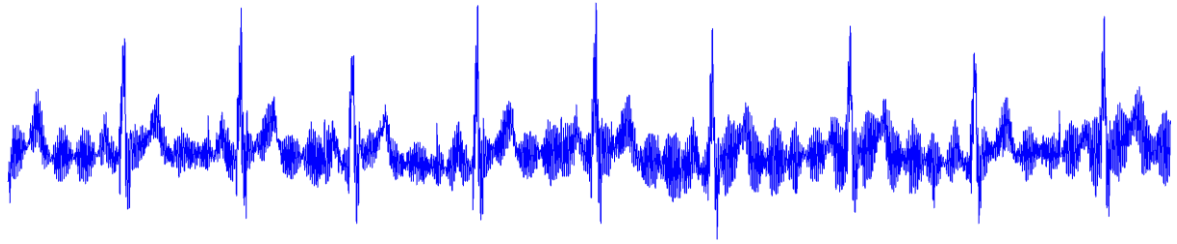
(a) Mains interference
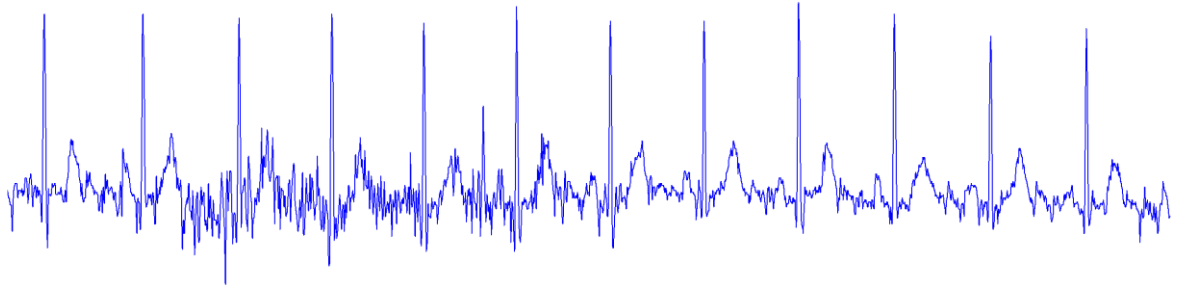
(b) Muscle artefact
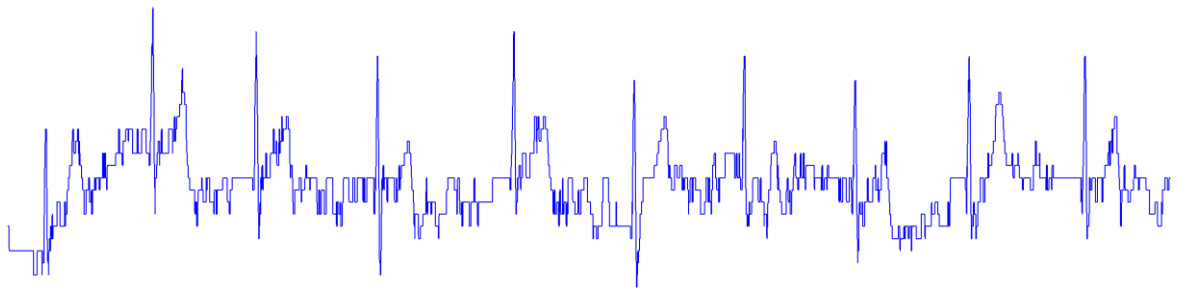
(c) Electrode contact noise
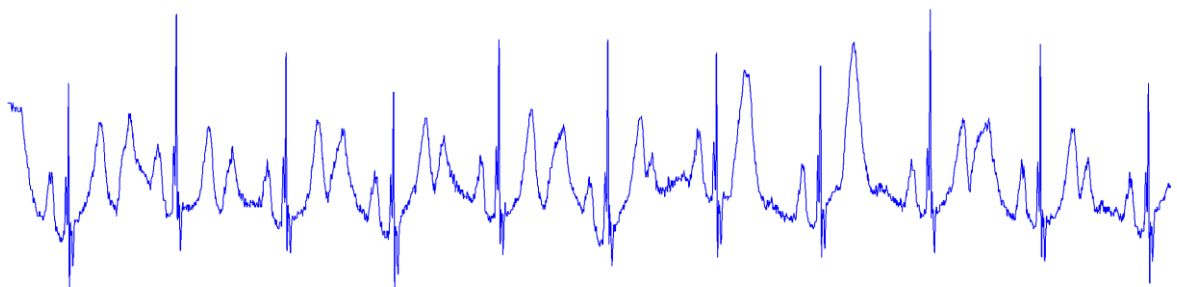
(d) Movement artifact

Figure 2.1: Examples of the different types of noise sources which can affect ECG signals.

Electrocardiogram traces used for identification are obtained using surface electromyography (EMG), where electrodes are placed on the skin in the vicinity of the heart. Potential differences of 1 to 3 mV generated at the body surface by the current sources in the heart are picked up by the electrodes and are amplified in order to improve the signal to noise ratio (SNR). The ECG waveform is observed on an oscilloscope or is digitized for further processing by a computer. The digitization process should use a sampling rate of at least 1 kHz to ensure that the ECG trace is of a high enough resolution as required for biometric purposes .

ECG measurements may be corrupted by many sorts of noise. The ones of primary interest are:

1. Power line interference,
2. Electrode contact noise,
3. Motion artifacts,
4. EMG noise, and
5. Instrumentation noise
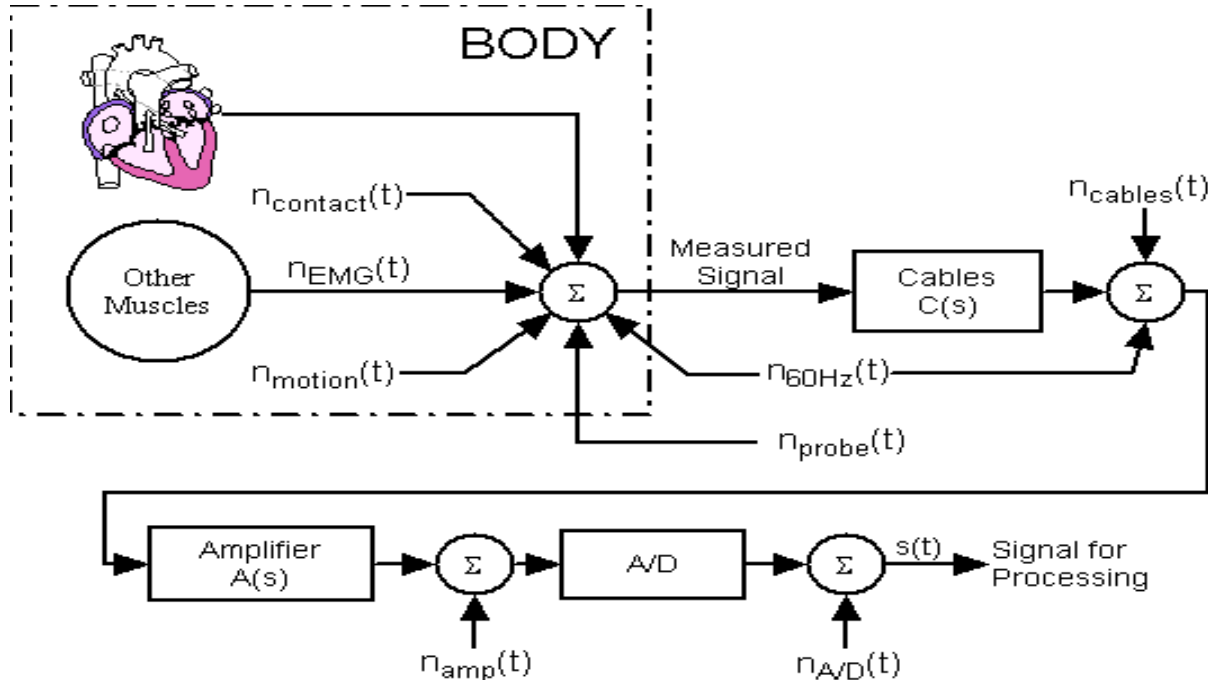
Figure. 2.2. Principal noise sources in electrocardiology**.**

2.1.1. <u>Power Line Interference:-</u>

Plotting a Fourier power spectrum of a typical ECG signal (Fig. 4) reveals various common ECG frequency components. Several interesting features are readily identifiable:

- The 1.2 Hz heart beat information (approximately 72 beats per minute)
- The 60 Hz power line interference

The remainder of the frequency components represents the subject information (situated between 0.1 Hz and 40 Hz) and contributions of other noise sources.
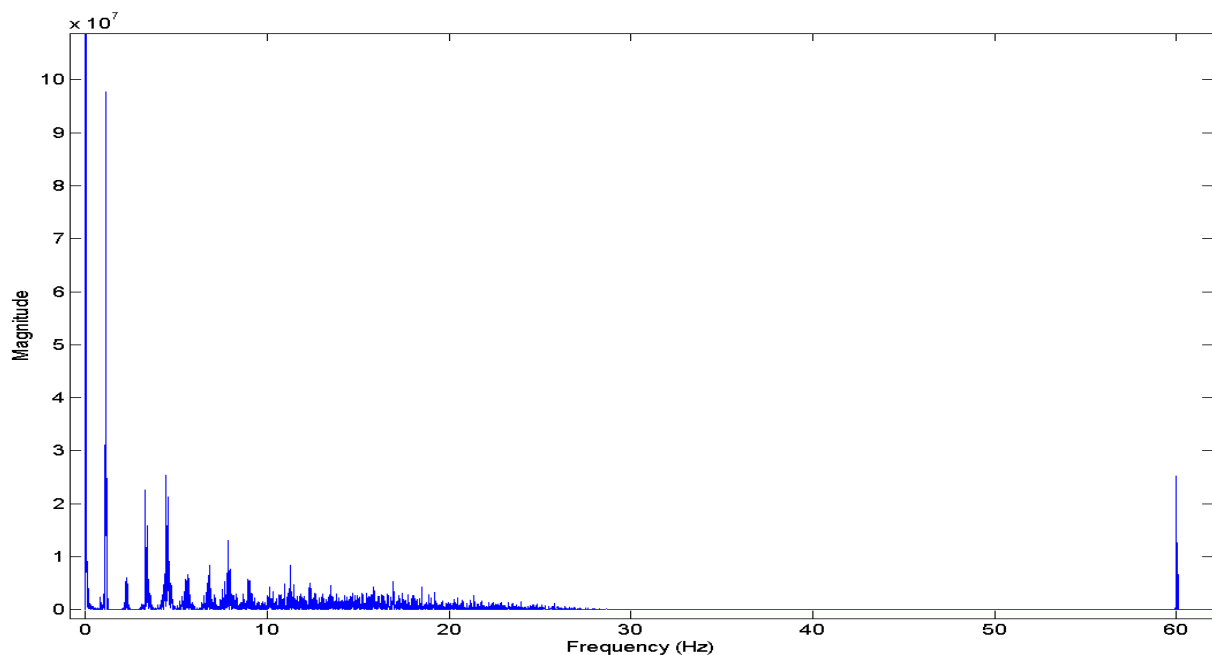
Figure. 2.3. Fourier power spectrum of an ECG trace. The 60 Hz power line interference and the baseline potential drift noise (at approximately 0 Hz) are identifiable.

Power line interference occurs through two mechanisms: capcaitive and inductive coupling. Capacitive coupling referes to the transfer of energy between two circutis by means of a coupling capacitance present between the two ciriuits. The value of the coupling capacitance decreases with increasing separtion of the circuits. Inductive coupling on the other hand is caused by mutual inducatance between two conductors. When current flows through wires it produces a magnetic flux, which can induce a current in adjacent cirucits. The geometry of the conductors as well as the separtion between them determines the value of the mutual inductance, and hence the degree of the inductive coupling. Typically, capacitive coupling is responsible for high frequency noise while inductive coupling introduces low frequency noise. For this reason **inductive coupling is the dominant mechanism of power line interference** in electrocardiology. Ensuring the electrodes are applied properly, that there are

no loose wires, and that all components have adequate shielding should help limit the amount of power line interference.The manifestation of power line noise can be modeled by

$$n_{60Hz}(t) = A\sin(2\pi \cdot 60 + \Omega)$$.

The average peak value, A, of the noise depends on the amount of coupling between the ECG equipment and the power lines, and will vary between measurements. During measurement the peak-to-peak value is also liable to fluctuate due to changing environmental conditions, which influence the amount of inductive or capacitive coupling of power lines to the ECG equipment. The phase of the sinusoid, represented by Ω in above equation , is a random variable with a uniform distribution in the range [-π, π). This simplistic model assumes that the noise will occur only at 60 Hz, but in reality the power line noise will have a finite bandwidth around its nominal center frequency, suggesting that the total noise is composed of many sinusoids of similar frequency.

2.1.2. Electrode Contact Noise and Motion Artifacts:-

Electrode contact noise is caused by variations in the position of the heart with respect to the electrodes and changes in the propagation medium between the heart and the electrodes. This causes sudden changes in the amplitude of the ECG signal, as well as low frequency baseline shifts. In addition, poor conductivity between the electrodes and the skin both reduces the amplitude of the ECG signal and increases the probability of disturbances (by reducing SNR). The underlying mechanism resulting in these baseline disturbances is electrode-skin impedance variation. The larger the electrode-skin impedance, the smaller the relative impedance change needed to cause a major shift in the baseline of the ECG signal. If the skin impedance is extraordinarily high, it may be impossible to detect the signal features reliably in the presence of body movement. Sudden changes in the skin-electrode impedance induce sharp baseline transients which decay exponentially to the baseline value. This transition may occur only once or rapidly several times in succession. Characteristics of this noise signal include the amplitude of the initial transition and the time constant of the decay.

Loose Contact
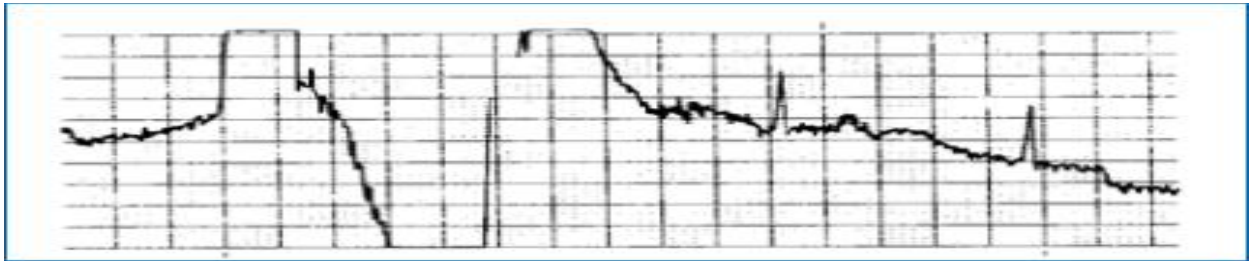
Motion Artifact
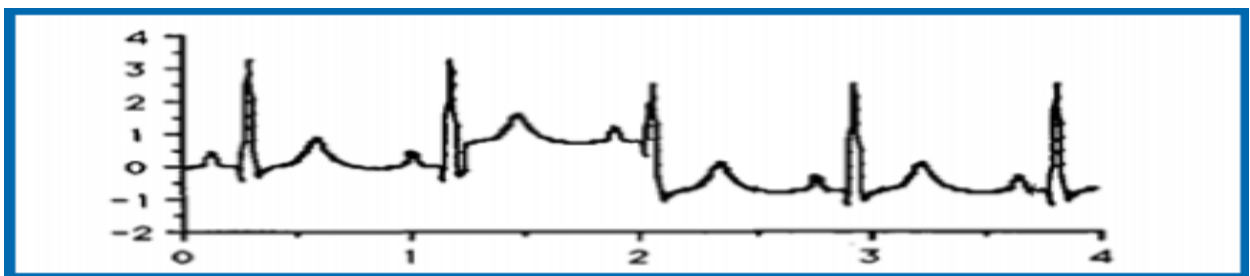
Baseline Drift due to respiration
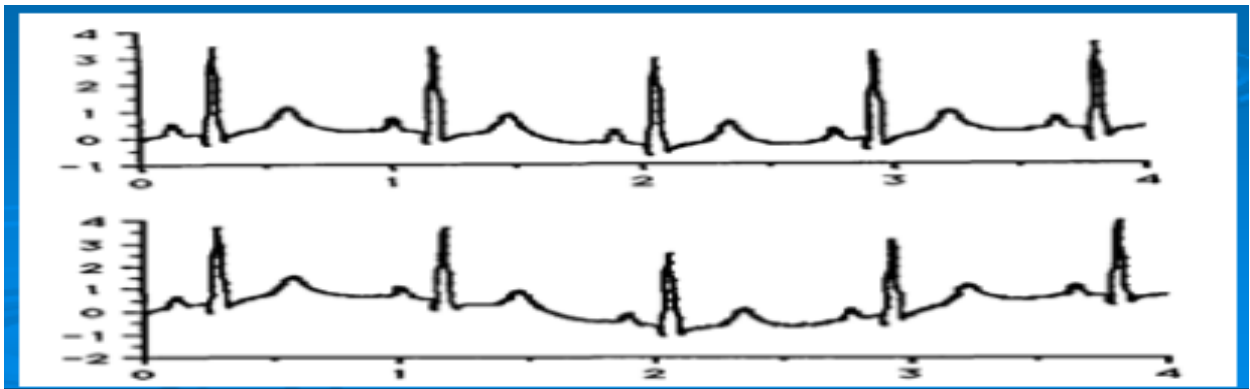
2.1.3. EMG Noise:-

EMG noise is caused by the contraction of other muscles besides the heart. When other muscles in the vicinity of the electrodes contract, they generate depolarization and repolarization waves that can also be picked up by the ECG. The extent of the crosstalk

depends on the amount of muscular contraction (subject movement), and the quality of the probes.

Amplitude ~ 10% of ECG

Broadband ~ (20-1000 Hz)

It is well established that the **amplitude of the EMG signal** is stochastic (random) in nature and can be **reasonably modeled by a Gaussian distribution function**. The mean of the noise can be assumed to be zero; however, the variance is dependent on the environmental variables and will change depending on the conditions. Certain studies have shown that the standard deviation of the noise is typically 10% of the peak-to-peak ECG amplitude. While the actual statistical model is unknown, it should be noted that the electrical activity of muscles during periods of contraction can generate surface potentials comparable to those from the heart, and could completely drown out the desired signal. The effects of typical EMG noise can be observed in the ECG signal shown in Fig. 2.3, and is particularly problematic in the areas of the P and T complexes. This noise is modeled by $n_{EMG}(t)$ in
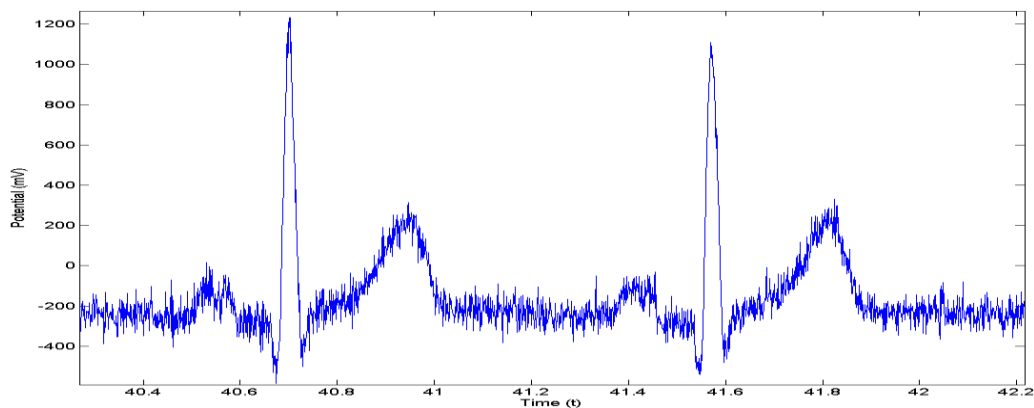
Figure. 2.4. Two second segment of an ECG trace. The *x*-axis is time in seconds, and the *y*-axis is the electrical potential in mV. Exact positions of P and T complexes are obscured be presence of EMG noise.

2.4. **Instrumentation Noise:-**

The electrical equipment used in ECG measurements also contributes noise. The major sources of this form of noise are the electrode probes, cables, signal processor/amplifier, and the Analog-to-Digital converter, represented respectively by $n_{probe}(t)$, $n_{cables}(t)$, $n_{amp}(t)$, **and** $n_{A/D}(t)$ in Fig. 2.1. Since this form of noise is usually defined by a white Gaussian distribution, Fig. 2.1 adequately represents its effects on the ECG signal. Unfortunately

instrumentation noise cannot be eliminated as it is inherent in electronic components, but it can be reduced through higher quality equipment and careful circuit design. One type of electrical noise is resistor thermal noise (also known as Johnson noise). This noise is produced by the random fluctuations of the electrons due to thermal agitation. The power spectrum of this noise is given by

$$\overline{V}_n^2 = 4kTR$$

This equation suggests that the resistor thermal noise is white for all frequencies; however, at frequencies larger than 100 THz the power spectrum starts to drop off. For our purposes we can assume the **resistor thermal noise to be band limited white noise.** This type of noise is generated in the electrodes, in the wire leads connecting electrodes to the amplifier, and in all the resistive electronic components internal to the ECG instrumentation. Since the magnitude of this noise component is substantial relative to the measured signal, its effects are most noticeable in the electrodes and any other electronic equipment prior to the amplifier.

Another form of noise, called flicker noise, is very important in ECG measurements, due to the low frequency content of ECG data. The actual mechanism that causes this type of noise is not yet understood, but one widely accepted theory is that it is caused by the energy traps which occur between the interfaces of two materials. It is believed that the charge carriers get randomly trapped/released and cause flicker noise. For MOSFET devices, the power spectral density of flicker noise is given by,

$$\overline{V}_{1/f}^2 = \frac{4kT}{WLC_{ox}f} ,$$

where k is the Boltzmann's constant, T is the temperature, C_{ox} is the silicon oxide capacitance, WL is the transistor area, and f is the frequency . As the equation suggests, flicker noise is inversely proportional to frequency, indicating that it becomes dominant at lower frequencies. It can be found in any electronic equipment which utilizes bipolar or metal oxide transistors, such as the amplifier used for signal amplification (or more specifically any device which has material junctions). Flicker noise contributions would be most noticeable at the electrodes since the amplitude of the detected signal is on the order of millivolts.

Chapter 3
Literature Survey

3.1. ECG Denoising Using Empirical Mode Decomposition:-

 The major advantage of EMD is that the basis functions used to decompose a signal are not predefined but adaptively derived from the signal itself. Direct application of EMD on ECG signal will not give the desired result due to the physiological characteristic of ECG .

The Cardiac components overlap with noncardiac contaminants (noise) in the frequency range of 0.01Hz to 100Hz because of which linear filtering (eg. Low-pass, band pass filters) cannot be applied to eliminate noisy components while keeping the desired components unchanged.

Its essence is to identify the intrinsic oscillatory modes by their characteristic time scales in the signal empirically, and accordingly decompose the signal into intrinsic mode functions (IMFs) by means of a *sifting* process. Therefore, EMD is especially applicable for nonlinear and nonstationary signals, including ECG.

IMF (Intrinsic Mode Function) represents the oscillating mode embedded in the original data. By definition, an IMF should satisfy two conditions:

 (1) the total number of local extrema and that of zero crossings should be equal to each other or different by at most one, and

 (2) the mean of the upper and lower envelopes respectively defined by local maxima and local minima should be zero.

3.1.1. Decomposition of Signal into IMF:-

✓ Identify all the local extrema, then connect all the local maxima by a cubic spline line to form the upper envelope.

✓ Repeat the procedure for the local minima to produce the lower envelope.

- ✓ Their mean is designated as m_1, as shown in Fig.
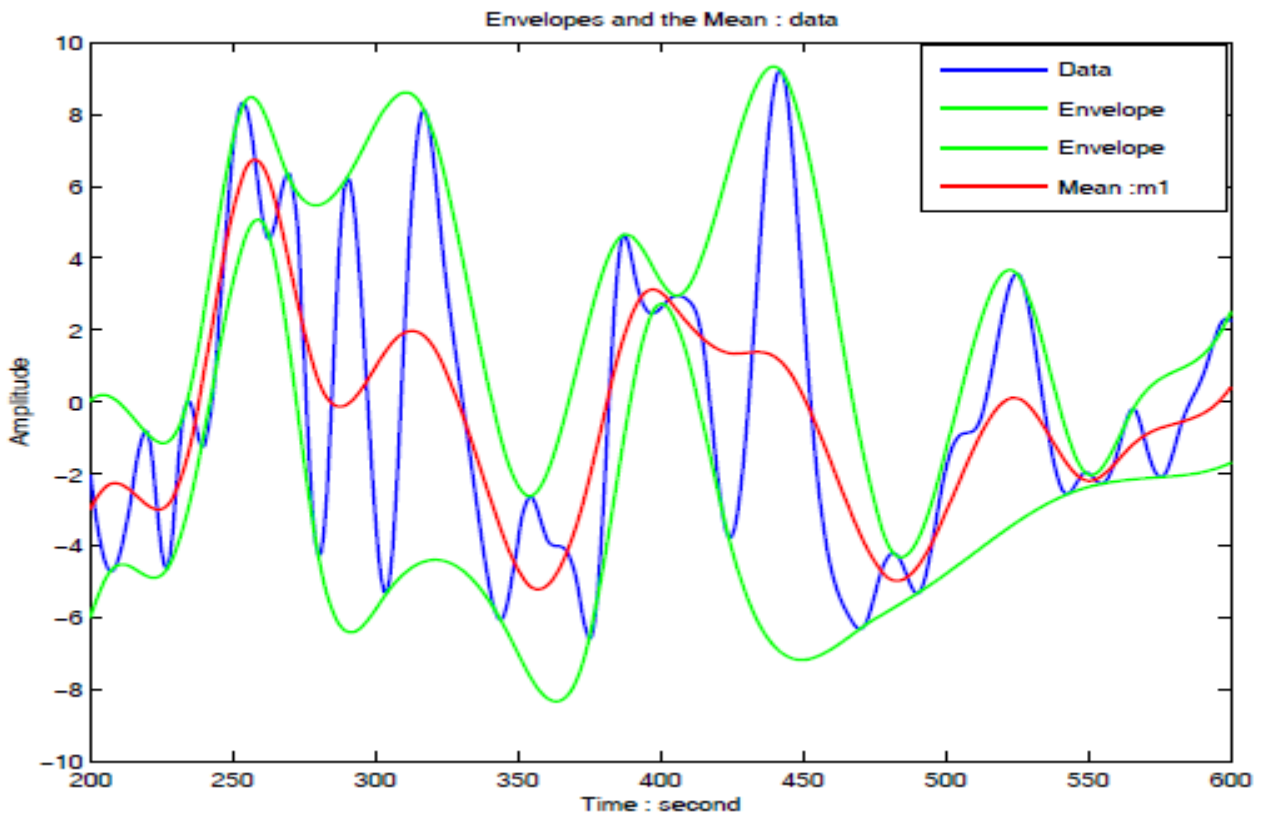
Figure3.1 Resultant Ecg After Applying The IMF Decompose

The difference between the data and m_1 is the first component h_1 -

i.e., $h_1 = x(t) - m_1$

The sifting process has to be repeated as many times as is required to reduce the extracted signal to an IMF. In the subsequent sifting processes, h1 can be treated only as a proto-IMF. In the next step, it is treated as the data; then,

$$h_{11} = h_1 - m_{11}$$

After repeated siftings in this manner, up to k times, h1k becomes an IMF; that is,

$h_{1k} = h_{1(k-1)} - m_{1k}$

then, it is designated as $\qquad$ $c_1 = h_{1k}$

i.e. the first IMF component from the data. The stoppage criterion is determined by using a Cauchy type of convergence test. Specifically, the test requires the normalized squared difference between two successive sifting operations defined as

$$SD_k = \frac{\sum_{t=0}^{T} |h_{k-1}(t) - h_k(t)|^2}{\sum_{t=0}^{T} h_{k-1}^2}$$

to be small. If this squared difference SD_k is smaller than a predetermined value, the sifting process will be stopped.

Once $c_1(t)$ is obtained, it is then subtracted from the original data to get a residue $r_1(t)$:

$r_1(t) = X(t) - c_1(t)$

$c_1(t)$ represents the finest scale mode of oscillation, and $r_1(t)$ still contains useful information about longer time scale components. Therefore, the residue is treated as a new signal, and repeated sifting processes are conducted to obtain:

$r_2(t) = r_1(t) - c_2(t)$

.

.

.

$r_n(t) = r_{n-1}(t) - c_n(t)$

The whole process can be stopped when

(1) $c_n(t)$ or $r_n(t)$ is less than a predetermined threshold, or

(2) $r_n(t)$ becomes a constant or monotonic function.

Combining above 2 results we finally get the decomposition result :

$$x(t) = \sum_{j=1}^{n} c_j + r_n.$$

where the original signal is decomposed into n IMFs and one residue

3.1.2 Drawback of direct ECG Denoising by EMD:-

A noisy ECG signal is now generated by adding white noise to a clean one, and then decomposed by EMD as shown in Figure. The top two subfigures are respectively the clean and noisy ECGs, and below them are all the 10 IMFs.
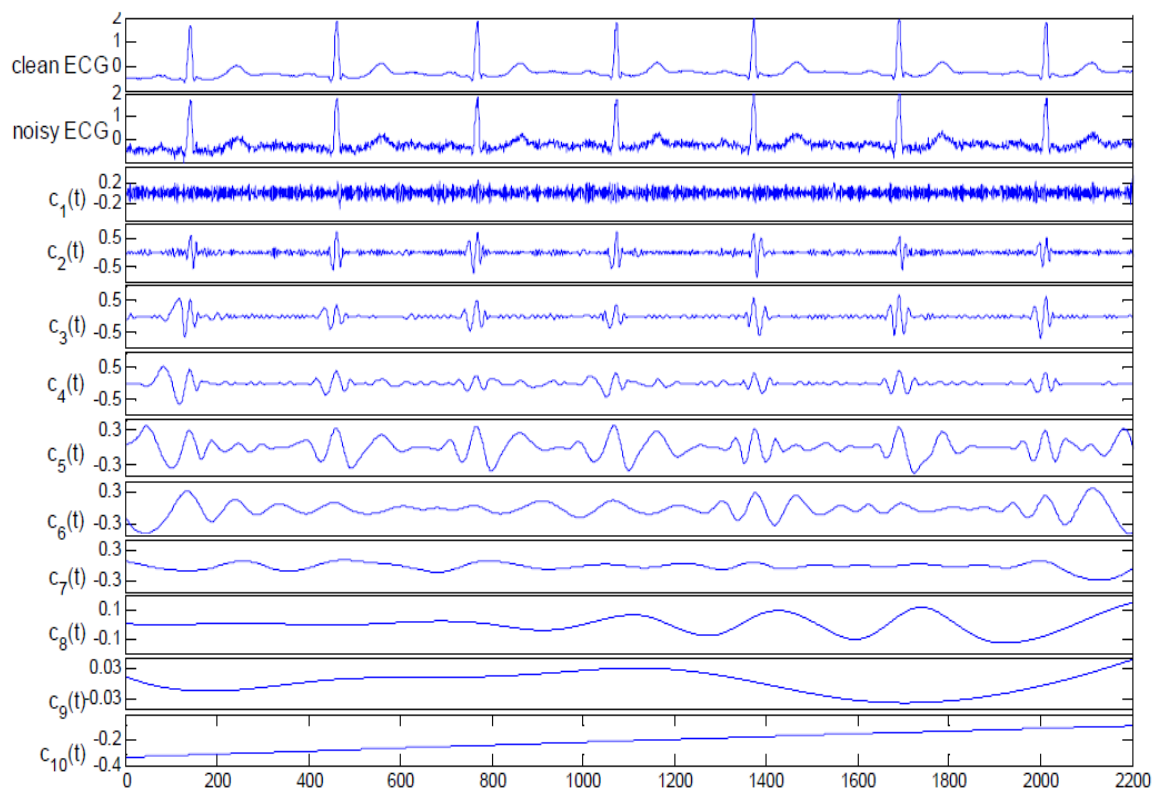
Figure 3.2. Noisy ECG and Decomposition result

If we simply discard the first IMF as noise, the output will still consist of considerable noise as in (a). If we remove the second IMF together, the resultant ECG will have the R waves heavily distorted as shown in (b).
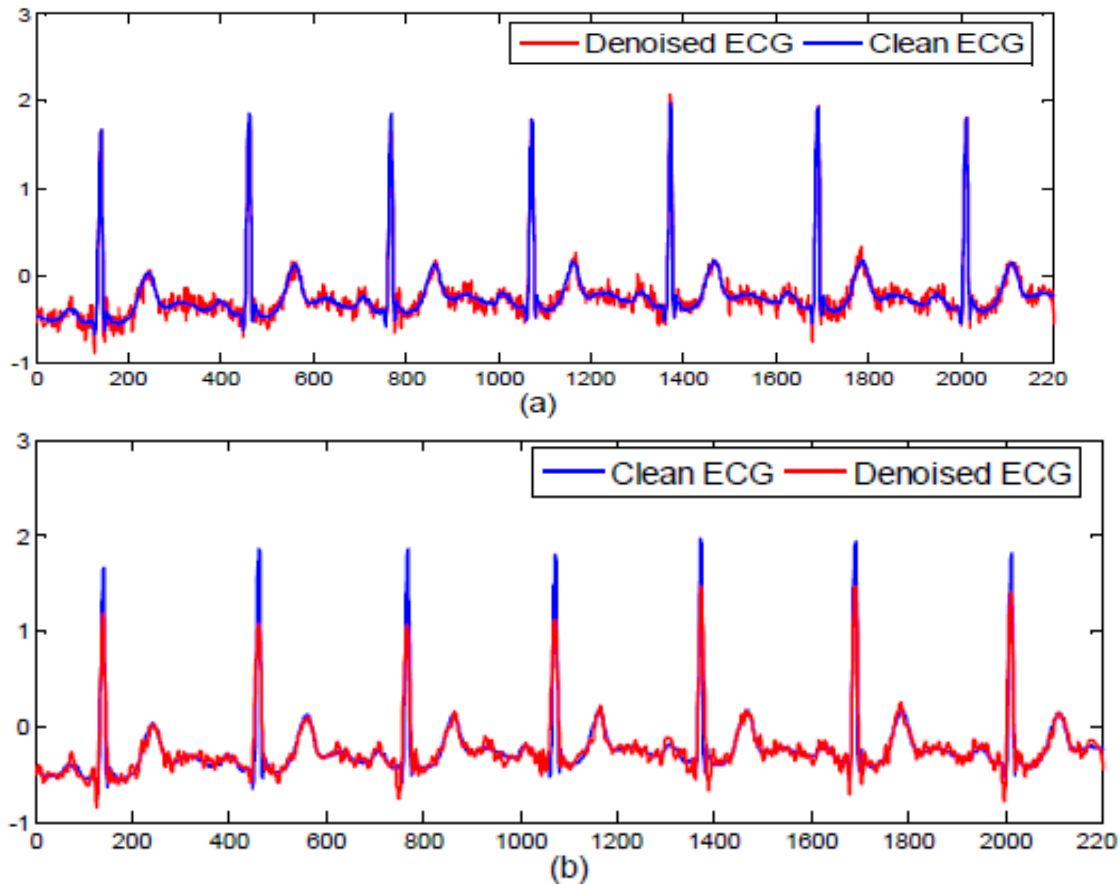
Figure 3.3. Clean Ecg Superimpose With Noisy Ecg

3.2 Denoising in ECG Signal Based on EMD and Adaptive Filter :-

➢ Least mean square (LMS) algorithm developed by Window and Hoff is the most widely used adaptive filtering algorithm which is simple and powerful.

➢ The coefficients are adjusted to minimize the meansquare error between its output and that of an unknown system.

➢ The filter consists of two main functional blocks: the reconstructed reference signal based on EMD and the adaptive unit based onLMS algorithm.
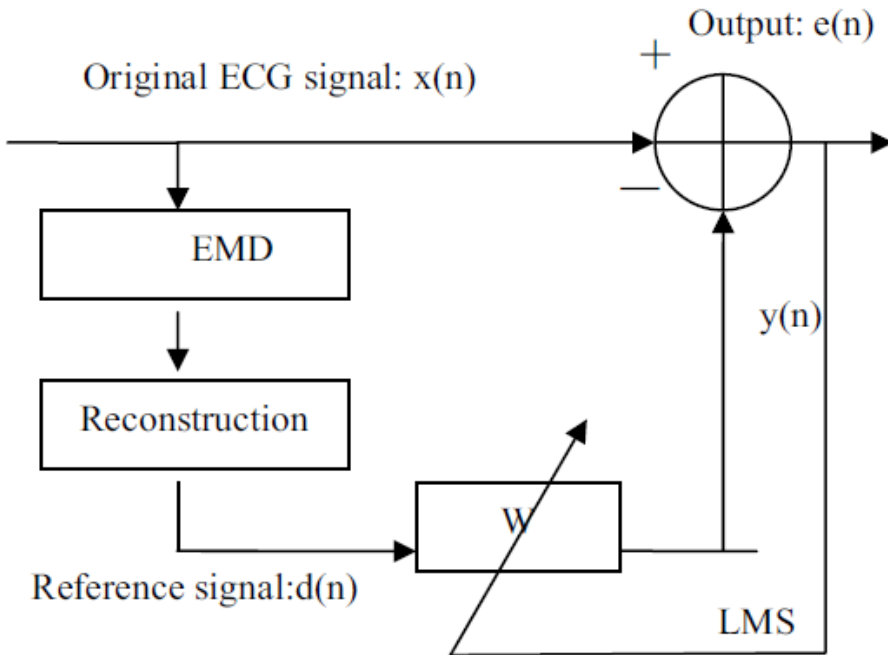
Figure 3.4. Block Diagram of Adaptive Filter

The power line interference can be roughly modeled by a sinusoidal signal which is actually one of the IMFs. Then the approximate power line interference can be acquired by the selective reconstruction of IMFs which can be regarded as the inference signal of adaptive filter.

If the original signal x(t) decomposed by EMD can be expressed as follows:

$$x(t) = \sum_{i=1}^{N} c_i(t)$$

the frequency of IMF $c_1(t)$, $c_2(t)$, .. $c_N(t)$ is decreasing. So the lowpass filter can be build as:

$$x_L(t) = \sum_{i=L}^{N} c_i(t) \quad 1 \leq L \leq N$$

the highpass filter can be expressed as:

$$x_H(t) = \sum_{i=1}^{H} c_i(t) \quad 1 \leq H \leq L$$

The generalized LMS algorithm of the adaptive filter

1. Initializes the W and the order of the filter is 1.

y(n) = d(n)W(n)

2. outputs:

e(n) = x(n) − y(n)

3. coefficient update:

W(n +1) = w(n) + 2μe(n)d(n)

The step-size μ directly affects how quickly the adaptive filter will converge.

✧ The first IMF seems to be a good representation of the power line interferences.
✧ If only the first IMF is filtered out, the reconstructed ECG will produce distortion of waveform.
✧ Therefore, the first IMF can be selected as the reference signal of the adaptive filter.

3.3 Model based ECG Denoising using EMD:-

➢ Firstly,we pre-filter the noisy ECG by making the model fit it in the MMSE sense, in order to preserve the important morphological features, especially the QRS complex.
➢ After that, the model is subtracted from the noisy ECG, and the residual signal is then decomposed using EMD and denoised by discarding the noise components from the decomposition results.
➢ Finally, the resultant ECG is obtained by combining the model and the denoised residue.

3.3.1 ECG dynamic model:-

A realistic synthetic ECG generator was first proposed by McSharry et al. [22], using a set of 3-D state equations to produce a trajectory in the Cartesian coordinates.

In essence, this model describes each feature wave (e.g. P, Q, R, S and T wave) of one ECG cycle by a Gaussian with three parameters: the amplitude a_i, width b_i, and location θ_i.

The vertical displacement of ECG is determined by an ordinary differential equation

$$\dot{z}(\theta) = - \sum_{i \in \{P,Q,R,S,T\}} a_i \frac{\Delta\theta_i}{b_i^2} \exp\left(-\frac{\Delta\theta_i^2}{2b_i^2} \right)$$

where $\Delta\theta = (\theta - \theta_i)$ and $\theta \in [0, 2\pi]$, since each cycle of ECG has been linearly mapped into the interval $[0, 2\pi]$ to handle the heart rate variation. A mathematical representation of one ECG cycle can be obtained by integrating the differential equation with respect to θ.

$$z(\theta) = \sum_{i \in \{P,Q,R,S,T\}} a_i \exp\left(-\frac{\Delta\theta_i^2}{2b_i^2} \right)$$

The model approximates an ECG cycle by the sum of five Gaussians with parameters describing wave amplitudes, widths and locations respectively, as shown
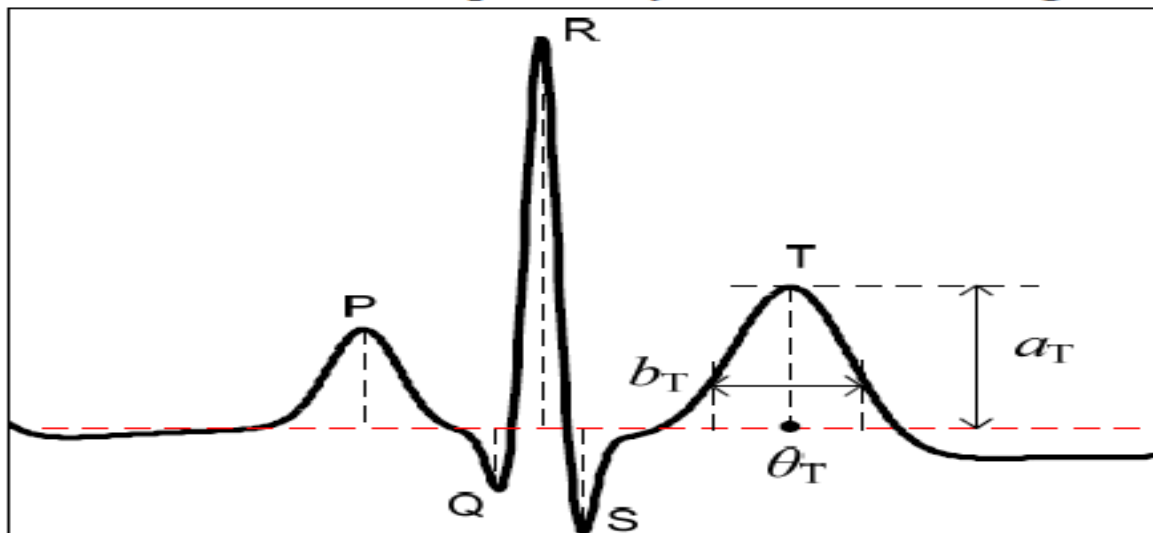
Figure3.5 Ecg Wavefrom With All Height

Sl.No	Noise Type	Filter used for denoising	Frequency Range
1	Baseline wander	High Pass Filter	Below 1 Hz
2	Power line interference	Band stop filter (3 order FIR filter)	50/60 Hz
3	Electromyographic noise (EMG noise)	Low Pass Filter	>100 Hz

Table 3.1 Adpative Filtering For Denoising

2 stages of model based denoising using EMD are :
   A. Model-based pre-filtering
   B. Denoising by EMD

A. Model-based pre-filtering

Clifford et al. [23] have demonstrated that this model can be used to filter a noisy ECG by fitting above equation to an ECG beat, and the filtered signal can preserve much clinical information, as illustrated in Fig
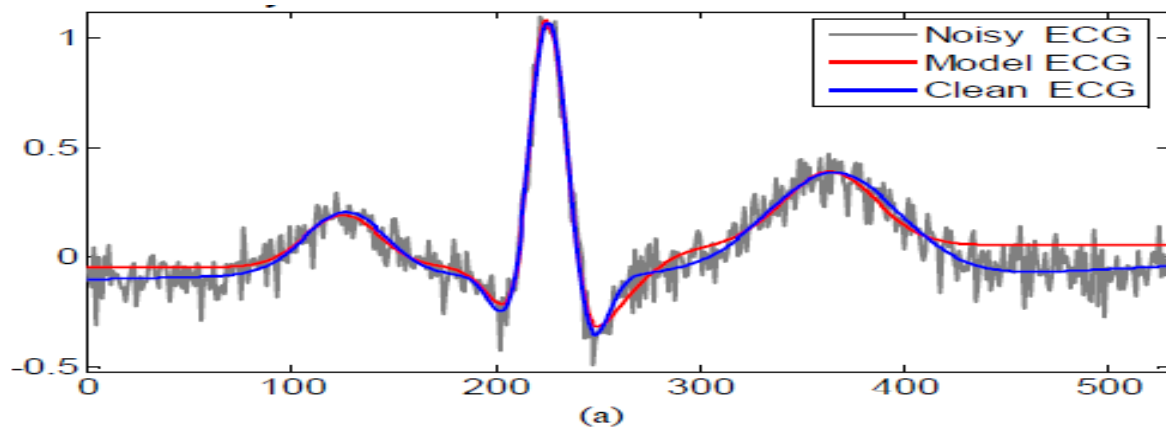
Figure 3.6 The ECG model $z(\theta)$ is fitted to a noisy signal $s(\theta)$

by minimizing the squared error between them. That is, we need to find

$$\min_{a_i, b_i, \theta_i} \left\| z(\theta) - s(\theta) \right\|^2$$

over all five $i \in \{P,Q,R, S,T\}$, with $\theta \in [0, 2\pi]$, and solve (8) by a gradient descent method in the parameter space. The Matlab function *lsqnonlin.m* can be applied to implementing this nonlinear optimization.

B. <u>Denoising by EMD</u>:-

➢ Since the fitted model has filtered and preserved the QRS complex very well, we only need to deal with the residue signal d2, which is now ready to be denoised by EMD.

➢ Firstly, d2 is decomposed into a set of IMFs

➢ we need to identify and discard IMFs that mainly contain noise components, and then add up all the other IMFs.

Significance IMF test procedure proposed by Flandrin et al. [24] through analyzing the EMD of fractional Gaussian noise.

Apart from the first IMF of the noise-only signal, the power spectra of the other IMFs exhibit self similar characteristics. Therefore, the logarithm of the k-th IMF energy E_k, i.e. $\log_2 E_k$, should linearly decrease with respect to k.

The IMF energies of a white-noise-only signal can be described approximately by:

$$E_k = (\sigma^2 2.01^{-k})/0.719 \qquad k = 2, 3, 4 \cdots$$

where σ^2 can be approximated by the variance of the first IMF of the noisy signal.

In Figure, the dashed line shows the relationship between log2Ek and k for a white noise model, while the solid line denotes the relationship for d2. The first 4 IMFs of d2 share similar energy

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distributions with those of the noise-only signal, but fromk=5, they diverge significantly from each other, indicating that the top 4 IMFs are primarily noise components and useful information is supposed to reside in the rest IMFs
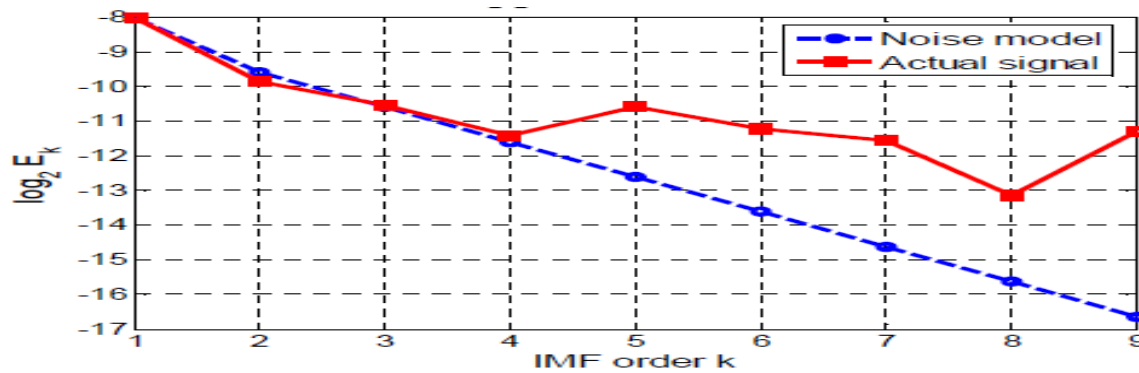
Figure 3.7 White Noise In Ecg

3.4. Independent Component Analysis:-

Independent Component Analysis (ICA) has been developed recently, which is a new method of Blind Source Separation.The aim of ICA is to separate mutually independent components from mixed signal, which is linear combination of a set of mutually independent source signals. With the characteristics of extracting the independent component, ICA has been widely applied in biomedical signal processing, mixed-signal separation, image de-noising and so on. ICA algorithm is applied to remove the interference of ECG signal, can not only preserve the original details information as soon as possible and filter the interference signal successfully.

ICA Model

Suppose, $x_1(t), x_2(t), x_3(t), ..., x_n(t)$ is a set of observed signals and

$s_1(t), s_2(t), s_3(t), ..., s_n(t)$ is a set of independent source signalsthen, the observed signals are given as:

$x_1(t) = a_{11} s_1(t) + a_{12} s_2(t) + ...a_{1m}s_m(t)$;

$x_2(t) = a_{21}\,s_1(t) + a_{22}\,s_2(t) + \ldots\ldots\ldots\ldots a_{2m}s_m(t)\ ;$

$\ldots\ldots\ldots\ldots$

$x_n(t) = a_{n1}\,s_1(t) + a_{n2}\,s_2(t) + \ldots\ldots\ldots\ldots a_{nm}s_m(t)\ ;$

Or, in Matrix form,

$$X = AS$$

Where $X = [x_1(t), x_2(t), \ldots\ldots x_n(t)]$ is an N- dimensional observed vector.

$S = [s_1(t), s_2(t), \ldots\ldots s_m(t)]$ is an M- dimensional unknown source signals vector.

$$A = \begin{bmatrix} a_{11}a_{12}\ldots a_{1m} \\ a_{21}a_{22}\ldots a_{2m} \\ \ldots\ldots\ldots\ldots \\ a_{n1}a_{n2}\ldots a_{nm} \end{bmatrix}$$ is an N x M mixing matrix.

Under the condition that both source signal S and mixing matrix A are unknown, the goal of ICA is to find a M×N separating matrix W for the signal x(t), which will make the outputs as independent as possible. The separated signals y(t) are derived from the mixture signal x(t) by separating matrix W. We can use the line transformation:

$$Y = WX$$

where, y (t) is an estimate of the sources s (t), W is the inverse of A.

From the above ICA model, we know that the sources S and mixing matrix A are unknown. It is impossible to obtain the sources just from the observed signals if without any transcendental Knowledge. In order to solve the problem, we do the following fundamental assumptions:

a) The components of s(t) are mutually independent.

b) The Hybrid method of sources is linear.

c) At most one of component of s is allowed to Gaussian. Because multi-Gaussian is still allowed to Gaussian, leading signal can't be distinguished.

d) The number of observed signal can't be less than the number of independent sources.

e) The average value of Sources is zero.

Fast ICA

ICA has many efficient algorithms, such as info-max, max- Entropy (ME), Minimum mutual information (MMI), maximum likelihood (ML) and Fast ICA and so on. But the fixed-point algorithm (Fast ICA) has been applied widely and conveniently and the program is also more mature than other algorithms.

Fast ICA - Algorithm

1. **Preprocess the data -** Before the FastICA algorithm can be applied, the input vector data **X** should be centered and whitened.

2. **2. Centering the data -** The input data is centered by computing the mean of each component of **X** and subtracting that mean. This has the effect of making each component have zero mean. Thus:

$$\mathbf{x} \leftarrow \mathbf{x} - E\{\mathbf{x}\}$$

3. **Whitening the data-**Whitening the data involves linearly transforming the data so that the new components are uncorrelated and have variance one. If $\widetilde{\mathbf{x}}$ is the whitened data, then the covariance matrix of the whitened data is the identity matrix:

$$E\{\widetilde{\mathbf{x}}\widetilde{\mathbf{x}}^T\} = \mathbf{I}$$

This can be done using eigenvalue decomposition of the covariance matrix of the data: $E\left\{\mathbf{xx}^T\right\} = \mathbf{EDE}^T$, where $\mathbf{E}$ is the matrix of eigenvectors and $\mathbf{D}$ is the diagonal matrix of eigenvalues. Once eigenvalue decomposition is done, the whitened data is:

$$\mathbf{x} \leftarrow \mathbf{D}^{-1/2}\mathbf{E}^T\mathbf{x}$$

Single component extraction

The iterative algorithm finds the direction for the weight vector $\mathbf{w}$ maximizing the non-Gaussianity of the projection $\mathbf{w}^T\mathbf{x}$ for the data $\mathbf{X}$. The function $g(\cdot)$ is the derivative of a nonquadratic nonlinearity $f(\cdot)$. Hyvärinen states that good values for f (shown with their derivatives g and second derivatives g') are:

$$f(u) = \log\cosh(u); \quad g(u) = \tanh(u); \quad g'(u) = 1 - \tanh^2(u)$$
$$f(u) = -e^{-u^2/2}; \quad g(u) = ue^{-u^2/2}; \quad g'(u) = (1 - u^2)e^{-u^2/2}$$

The first equation is a good general-purpose equation, while the second is highly robust.

Randomize the initial weight vector $\mathbf{w}$

Let $\mathbf{w}^+ \leftarrow E\left\{\mathbf{x}g(\mathbf{w}^T\mathbf{x})\right\} - E\left\{g'(\mathbf{w}^T\mathbf{x})\right\}\mathbf{w}$

Let $\mathbf{w} \leftarrow \mathbf{w}^+/\|\mathbf{w}^+\|$

If not converged, go back to 2

Multiple component extraction

The single unit iterative algorithm only estimates one of the independent components, to estimate more the algorithm must repeated, and the projection vectors decorated. Although Hyvärinen provides several ways of decorating results the simplest multiple unit algorithm follows. $\mathbf{1}$ indicates a column vector of 1's with dimension M.

Algorithm FastICA

Input: C Number of desired components

Input: $\mathbf{X} \in \mathbb{R}^{N \times M}$ Matrix, where each column represents an *N*- dimensional sample, where

$C < N$

Output: $\mathbf{W} \in \mathbb{R}^{C \times N}$ Un-mixing matrix where each row projects X onto into independent component.

Output: $\mathbf{S} \in \mathbb{R}^{C \times M}$ Independent components matrix, with M columns representing a sample with C dimension

Pseudo Code

for p **in** 1 to C:

$\quad \mathbf{w_p} \leftarrow$ *Random vector of length N*

while $\mathbf{w_p}$ changes

$$\mathbf{w_p} \leftarrow \mathbf{w_p} - \sum_{j=1}^{p-1} \mathbf{w_p}^T \mathbf{w_j} \mathbf{w_j}$$

$$\mathbf{w_p} \leftarrow \frac{\mathbf{w_p}}{\|\mathbf{w_p}\|}$$

Output:
$$\mathbf{W} = \begin{bmatrix} \mathbf{w_1} \\ \vdots \\ \mathbf{w_C} \end{bmatrix}$$

Output: $\mathbf{S} = \mathbf{W}\mathbf{X}$

Advantages of Fast - ICA

Compared with other ICA algorithm, FastICA has the following advantages:

1) Cubic convergence, with faster Convergence speed than other linear convergence algorithm.

2) Needn't choose Learning step and other parameters, more reliable and Easier to use.

3) Component can be extracted including sub-Gaussian and super-Gaussian sources.

4) Independent component can be estimated one by one and have many advantages of nerve algorithms, such as parallel processing, small memory demanding

Application of ICA model in ECG signal processing

As ECG signal and power-line interference are caused by different independent sources, So It can be thought that they are mutually independent. Secondly, the Hybrid method of observed sources is linear .In addition, Strictly speaking, Both the ECG signal and interference are not Gaussian signal. Thus, the forward three conditions of ICA have been satisfied. For the forth condition, can be met by adding the number of channels. For ease of calculation. Make M = N. Hence, power line interference can be eliminated from the source signal using the ICA model. ICA model of Removal power line interference is shown in figure :
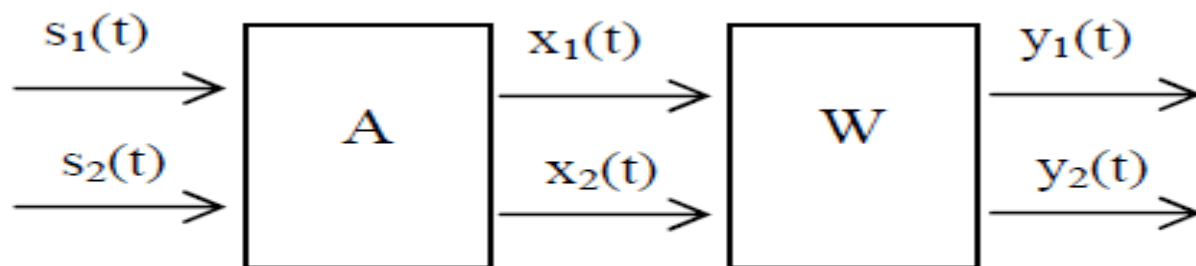
Figure . ICA model of Removal power line interference

Where, s1(t) is the original ECG signal without interference, s2(t) is 50HZ power line interference, which are two independent sources signal. x1(t) is the observed ECG signal with interference, x2(t) is the measured power line interference, which are two observed signals. y1(t), y2(t) are independent ECG signal and power line interference after separated by ICA algorithm. Empirical mode decomposition (EMD) is an excellent tool for analyzing non stationary and non linear data, and can easily be applied to biomedical signal denoising. However, direct EMD denoising is not suitable for ECG,for the R wave is quite high and sharp, and therefore easily deformed. Considering the simpleness and flexibility of the ECG model, we use it to pre-filter

the ECG and thus preserve the feature waves of ECG, then apply EMD to denoise the residual signal, and finally combine the model and the denoised residue. As a new signal processing technology, ICA theoretical system is not perfect, some practical issues have yet to be further resolved. Such as, the order of output component is uncertain, when the Hybrid of source signal is Nonlinear and the number of observed signal is less than number of source signal. Wavelet Transformation technique, ECG Modelling technique combined with EMD as well as Adaptive Filtering technique for the processing of ECG signals are very robust and performs good under all sorts of noises possible in ECG signal. That why I used wavelet functions for denoising the ecg signal.

Chapter 4
Methodology

Our work basically includes three phases namely de-noising of the input signal, detection of peaks and finally detecting the abnormality if any present. The classification of the detected abnormality in the ECG beats is done by prior medical knowledge regarding the techniques of reading the ECG along with the signal processing techniques. The presence of noises in ECG signals will severely affect the visual diagnosis and feature extraction of various applications (stress measurement, emotion estimation and human computer interfaces, etc.). The presence of parasite interference signals could cause serious problems in the registration of ECG signals and many works have been done to suppress electromyogram (EMG) artifacts noises and disturbances from electrocardiogram (ECG). In general, ECG signals are affected by noises such as baseline wandering, power line interference, electromagnetic interference, and high frequency noises during data acquisition. The main problem of digitalized signal is interference with other noisy signals like power supply network 50 Hz frequency and breathing muscle artefacts [25]. These noisy elements have to be removed before the signal is used for next data processing like heart rate frequency detection. In order to eliminate the noises and to extract the efficient morphology of ECG signals, several pre-processing methods have been proposed over past few decades [26]. Hence, this is the method used by us in the ECG signal processing, specifically for de-noising of the original signal. The wavelet transform gave us the best results and noise was completely removed from the original signal.

Wavelet transform is an effective tool for feature extraction, because they allow analysis of images at various levels of resolution I have considered the Discrete Wavelet Transform (DWT) based wavelet de-noising have incorporated using four different thresholding techniques to remove three major sources of noises from the acquired ECG signals namely, power line interference, baseline wandering, And high frequency noises.seven wavelet functions ("db1","coif1","rbio1.1","dmey","bior1.1","haar" and "sym1") and four different thresholding levels are used to de-noise the noise in ECG signals.

This resulted in the production of smooth ECG signals which truly ameliorated the process of extraction of ECG data (detection of peaks and peak to peak intervals).

The aim of our project was to process the ECG signals (make them noise-free), detect the peaks of the ECG waveform and check whether the signal is normal or abnormal. Also, if the signal is abnormal, the software should show the probable heart disease present in the patient.

With this aim, I did an extensive literature survey which involved an exhaustive search for available research papers, databases and related information. The survey was done with core depth and it was always kept in mind that no relevant information was missed out. Popular databases which contain information about the ECG signals (both normal and abnormal) were carefully examined and valuable information was gathered. Various reputed journals were regularly reviewed and any relevant information from the field of Bio-medical Engineering was retrieved. After an exhaustive literature survey, we gathered sufficient data of various ECG signals, both normal and abnormal. After searching on the net and reviewing various research papers regarding ECG signal processing and analysis, we finally decided on the MIT-BIH arrhythmia database as it was the most reputed and reliable database available. It has about 500 samples of ECG signals and hence, data screening was very important.

4.1 <u>Wavelet Transform</u>:-

A wavelet is a "small wave" of varying frequency and limited duration.Using narrow windows for analyzing high frequencies and wide windows for analyzing low frequencies works quite well for signals having high frequency components for short durations and low frequency components for long durations.
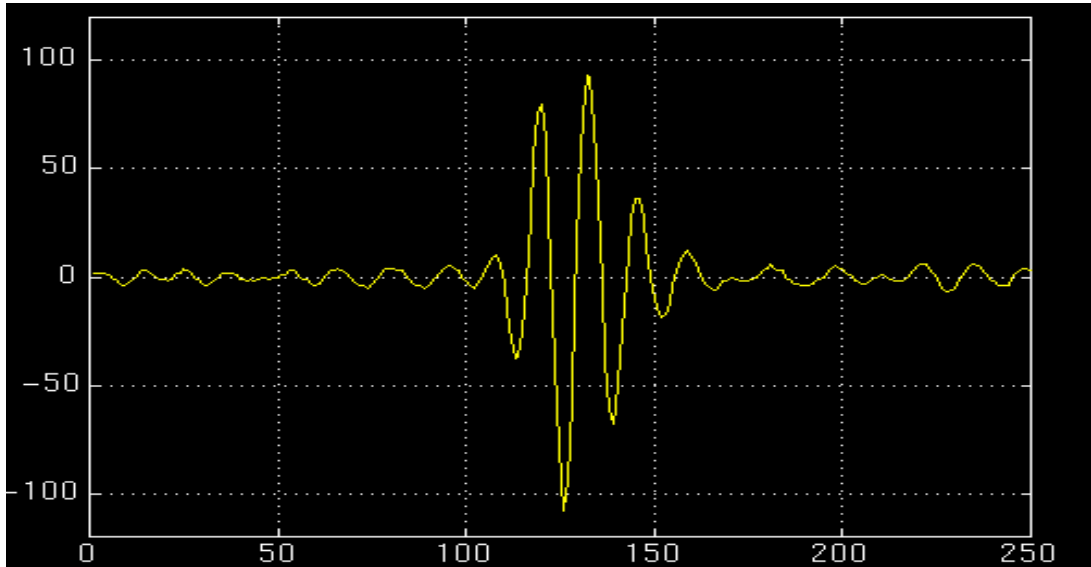
Figure. 4.1 Wavelet Function

$$CWT_f^{\psi}(\tau, s) = \frac{1}{\sqrt{s}} \int_t f(t)\psi^* \left(\frac{t-\tau}{s}\right) dt \qquad \text{(forward CWT)}$$

Translation parameter, measure of time

Scale parameter, measure of frequency

Normalization constant

Continuous wavelet transform of the signal *f(t)*

The mother wavelet. All kernels are obtained by translating (shifting) and/or scaling the mother wavelet .

Scale = 1/frequency

Wavelets provide simultaneous localization in time and scale (i.e, frequency).The location of the wavelet allows to explicitly represent the location of events in time. The shape of the wavelet allows to represent different detail or resolution.

.
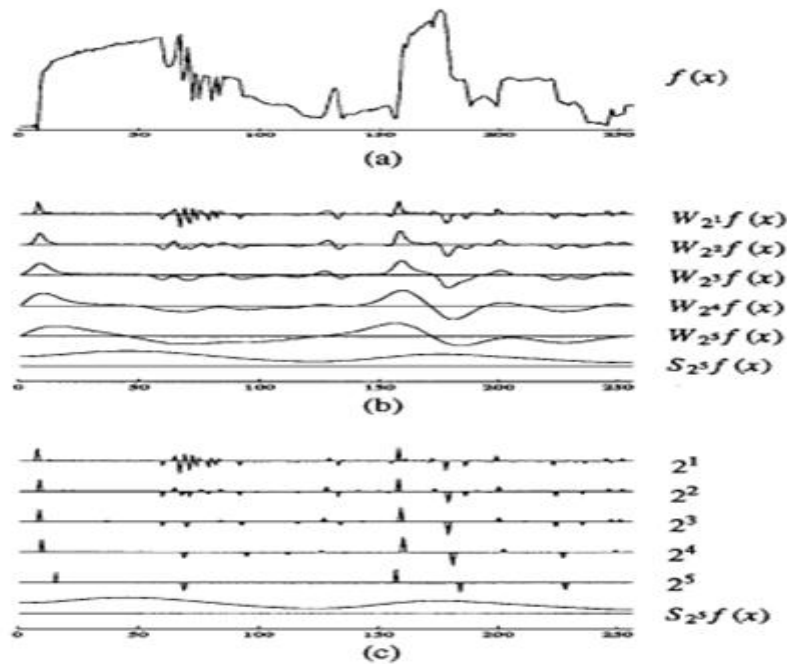
Figure4.2. (a): Image scan line of 256 samples. (b): Dyadic wavelet transform of signal 1(a), on 5 scale (2^5), we keep the remaining low-frequencies $S_2^5 f(x)$ to have the complete representation. (c): Maxima representation of wavelet transform shown in (b). Each dirac indicate the position and amplitude of local maxima at the corresponding scale of Dyadic wavelet transform.

$$f(t) = \sum_k c_k \varphi(t-k) + \sum_k \sum_j d_{jk} \psi(2^j t - k)$$

.... (4.1)

V_0

basis functions

$W_0, W_1, W_2, \ldots$

wavelet functions

4.2. Wavelet Transform in the Processing for ECG Signals:-

The basic idea is as follow: first of all, we make use of Wavelet Transform to scale decompose ECG signals with noises into different frequency band signals, then, we remove some "details" (a variety of noises), finally, we adopt the wavelet to reconstruct and restore useful signals to get ECG signals without noises. If the function

$\psi(t) \in L^2(R)$ and meets $\int_{-\infty}^{+\infty} \psi(t)dt = 0,$, then it is known as the mother wavelet or the basic wavelet.

The basis function of Wavelet Transform is known as the wavelet function, for short the wavelet, which is expressed $\psi_{a,b}(t)$ generated by the basic wavelet ψ *(t)* after companding and moving parallelly, as shown in the formula:

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

.... (4.2)

where *a* is the companding factor and *b* is the moving parallelly factor and $a \neq 0$, *a* and *b* are the continuous quantities.

$$W_f(a,b) = \langle f, \psi_{a,b} \rangle = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(t)\overline{\psi}\left(\frac{t-b}{a}\right)dt$$

.... (4.3)

where $a \neq 0$ and *a* and *t* are the continuous quantities and $\psi(t)$ is the conjugate of $\psi(t)$.

If the signal *f* *(t)* is reconstructed by the basic function of Wavelet Transform, its definition of inverse-transform is such as the formula

$$f(t) = \frac{1}{C_\psi} \iint_{\infty} \frac{W_f(a,b)\psi_{a,b}(t)}{a^2} dadb$$

$$C_\psi = \int_{+\infty}^{-\infty} \frac{\left|\overset{\wedge}{\psi}(w)\right|}{|w|} dw$$

.... (4.4)

where *w* is a continuous quantity and *(w)* ψ is Fourier Transform of ψ *(t)* .

The definition of equivalent frequency-domain of continuous Wavelet Transform is such as the Formula

$$W_f(a,b) = \frac{\sqrt{a}}{2\pi} \int_{-\infty}^{+\infty} \overset{\Lambda}{f}(w) \overset{\overline{\Lambda}}{\psi}(aw) \exp(jwb)dw$$

……… (4.5)

where $\overset{\Lambda}{f}(w)$ is Fourier Transform of $f(t)$ and $\overset{\overline{\Lambda}}{\psi}(w)$ is the conjugate of $\overset{\Lambda}{\psi}(w)$.

Wavelet Transform which decomposes the signal to the superimposition of a series of wavelet produced by the basic wavelet after companding and moving parallelly, is a localized time-frequency analysis method, that is, it has the lower temporal resolution and the higher frequency resolution in the low frequency part, and has the lower frequency resolution and the higher temporal resolution in the high frequency part. It has the the automatic adaptive characteristics for signals, which is particularly suited to deal with ECG signals.

4.3 Wavelet Threshold Value Eliminating Noises:-

In the wavelet domain, the signal energy relatively concentrates in a few locations, but noises distribute more widely. According to the transient nature, signals ofen representate some big coefficients, and some small coefficients are generated by the mutation of noises and the signal energy, so the wavelet threshold value eliminating noises mainly uses the different performance characteristics of singularity of effective signals and noises in Wavelet Transform to eliminate noises and retain effective signals, and it has more obvious advantages more than traditional methods.The same signal when processed with different wavelet functions gets different results, so the selection of wavelet funtion is very important. Based on the characteristics of the ECG signal, most appropriate Wavelet functions that can be applied are: Coiflets wavelet, Daubechies wavelet and Symlets wavelet,"rbio1.1" ,"dmey" ,"bior1.1","haar". The explained Wavelet Denoisig Algorithm given below[32].

Example:

Suppose we are given a 1D "image" with a resolution of 4 pixels:[9 7 3 5]

This image can be represented in the Haar basis as follows:

Start by averaging the pixels together (pairwise) to get a new lower resolution image:

[8 4] (averaged and subsampled)

To recover the original four pixels from the two averaged pixels, store some *detail coefficients*.

Resolution	Averages	Detail Coefficients
4	[9 7 3 5]	[]
2	[8 4]	[1 − 1]

Repeating this process on the averages gives the full decomposition:

Resolution	Averages	Detail Coefficients
4	[9 7 3 5]	[]
2	[8 4]	[1 − 1]
4	[6]	[2]

The Haar decomposition of the original four-pixel image is:

$$[6 \quad 2 \quad 1 \quad -1]$$

We can reconstruct the original image to a resolution by adding or subtracting the detail coefficients from the lower-resolution versions.

$$= 8 \times \qquad \boxed{} \qquad \varphi_{0,1}(x)$$

$$+ 4 \times \qquad \varphi_{1,1}(x) \qquad \boxed{}$$

$$+ 1 \times \qquad \sqcap\!\sqcup \qquad \psi_{0,1}(x)$$

$$+ -1 \times \qquad \psi_{1,1}(x) \qquad \sqcap\!\sqcup$$

$$= 6 \times \qquad \boxed{} \qquad \varphi_{0,0}(x)$$

$$+ 2 \times \qquad \sqcap\!\!\!\sqcup \qquad \psi_{0,0}(x)$$

$$+ 1 \times \qquad \sqcap\!\sqcup \qquad \psi_{0,1}(x)$$

$$+ -1 \times \qquad \sqcap\!\sqcup \qquad \psi_{1,1}(x)$$
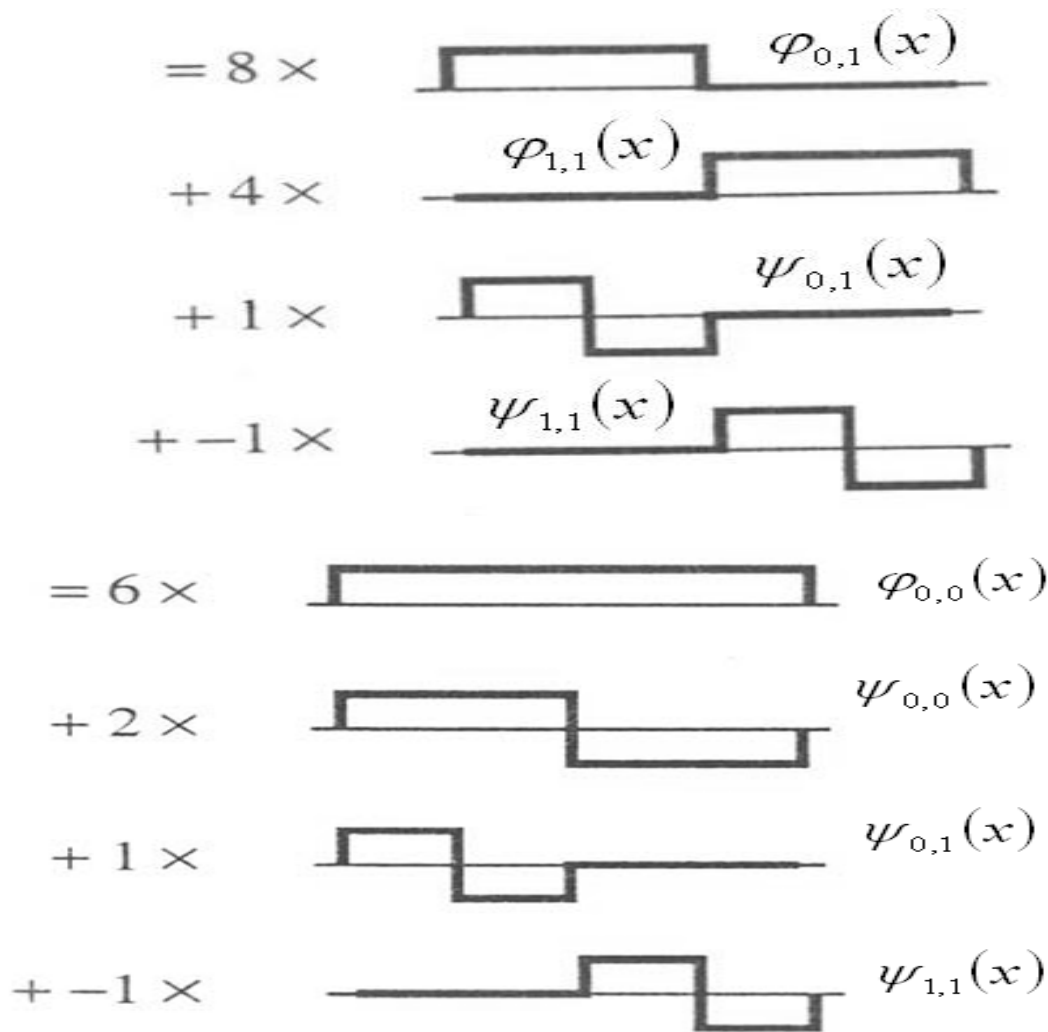
The earlier method of ECG signal analysis was based on time domain method. But this is not always sufficient to study all the features of ECG signals. So, the frequency representation of a signal is required. To accomplish this, FFT (Fast Fourier Transform) technique is applied. But the unavoidable limitation of this FFT is that the technique failed to provide the information regarding the exact location of frequency components in time. As the frequency content of the ECG varies in time, the need for an accurate description of the ECG frequency contents according to their location intime is essential. This justifies the use of time frequency representation in quantitative electro cardiology.

The wavelet transformation is based on a set of analyzing wavelets allowing the decomposition of ECG signal in a set of coefficients. Each analyzing wavelet has its own time duration, time location and frequency band. The wavelet coefficient resulting from the wavelet transformation corresponds to a measurement of the ECG

components in this time segment and frequency band, making it very suitable for analyzing non-stationary signals.

4.4. <u>Wavelet Analysis</u>:-

The theory of wavelet transform was developed in 1980s and has been widely used in image processing, theoretical physics, signal analysis, medical imaging, etc. [27]. It has been applied to remove the noises of ECG signal in recent years. Yu BC proposed a filtering method using the modulus maxima of wave translation. Then this method was replaced by neural network based adaptive filtering method introduced by Xue et al. Wavelet transform was used in ECG signal detection early successfully by Li et al [28]. The basic ideas behind it is as follows: From the equivalent filter of dyadic wavelet transform, the relationship between singularity of the signal (i.e. R-peak) and zero-cross points corresponding to its modulus maxima of wavelet transform was analyzed, then the ECG signal was decomposed into wavelets in different frequencies, and finally QRS complex as detected depending on the different distribution of ECG signal and noise spectrum in different frequency bands. Research shows that using wavelet transform to extract QRS complex has a high detection rate [29].The wavelets can broadly be classified into two major types: Continuous Wavelet transform (CWT) and Discrete Wavelet Transfor (DWT).

4.4.1. <u>Continuous Wavelet Transform (CWT)</u>:-

Wavelet transform can be defined as

$$[W_\psi f](a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} \overline{\psi\left(\frac{x-b}{a}\right)} f(x)dx$$

.... (4.6)

The wavelet coefficients c_{jk} are the given by

$$c_{jk} = [W_\psi f]\left(2^{-j}, k2^{-j}\right)$$

Here, $a = 2^{-j}$ is called the binary dilation or dyadic dilation, and $b = k2^{-j}$ is the binary or dyadic position [2], [28].
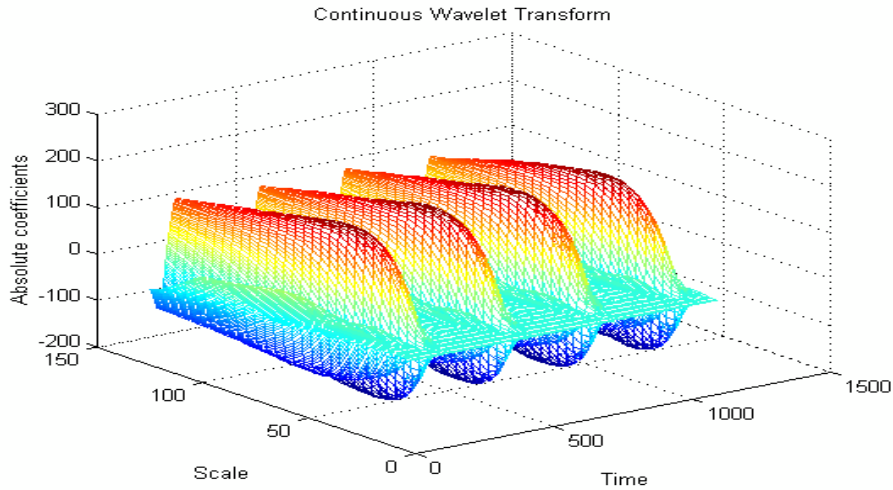
Figure4.3 continuous wavelet transform (CWT)

A continuous wavelet transform (CWT) is used to divide a continuous-time function into wavelets. Unlike Fourier transform, the continuous wavelet transform possesses the ability to construct a time-frequency representation of a signal that offers very good time and frequency localization. In mathematics, the continuous wavelet transform of a continuous, square-integrable function. $x(t)$ at a scale $a > 0$ and translational value $b \in \mathbb{R}$ is expressed by the following integral :

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

……… (4.7)

where $\psi(t)$ is a continuous function in both the time domain and the frequency domain called the mother wavelet and represents operation of complex conjugate [2]. The main purpose of the mother wavelet is to provide a source function to generate the daughter wavelets which are simply the translated and scaled versions of the mother wavelet. To recover the original signal $x(t)$, inverse continuous wavelet transform can be exploited.

$$x(t) = \int_0^\infty \int_{-\infty}^\infty \frac{1}{a^2} X_w(a, b) \frac{1}{\sqrt{|a|}} \tilde{\psi}\left(\frac{t-b}{a}\right) db \, da$$

.... (4.8)

$\tilde{\psi}(t)$ is the dual function of $\psi(t)$. And the dual function should satisfy

$$\int_0^\infty \int_{-\infty}^\infty \frac{1}{|a^3|} \psi\left(\frac{t_1-b}{a}\right) \tilde{\psi}\left(\frac{t-b}{a}\right) db \, da = \delta(t - t_1).$$

.... (4.9)

Sometimes,

$$\tilde{\psi}(t) = C_\psi^{-1} \psi(t),$$

Where

$$C_\psi = \frac{1}{2} \int_{-\infty}^{+\infty} \frac{\left|\hat{\psi}(\zeta)\right|^2}{|\zeta|} d\zeta$$
.... (4.10)

is called the admissibility constant and $\hat{\psi}$ is the Fourier transform of ψ [2]. For a successful inverse transform, the admissibility constant has to satisfy the admissibility condition: $0 < C_\psi < +\infty.$

It is possible to show that the admissibility condition implies that $\hat{\psi}(0) = 0$, so that a wavelet must integrate to zero [2].

Mother Wavelet:-

In general, it is preferable to choose a mother wavelet that is continuously differentiable with compactly supported scaling function and high vanishing moments. A wavelet associated with a multiresolution analysis is defined by the following two functions: the wavelet function $\psi(t)$, and the scaling function $\varphi(t)$.

The scaling function is compactly supported if and only if the scaling filter h has a finite support, and their supports are the same. For instance, if the support of the scaling function is [N1,N2], then the wavelet is [(N1-N2+1)/2,(N2-N1+1)/2]. On the other hand, the kth moments can be expressed by the following equation conditions of mother wavelet:[28]

1) admisibility 2) regularity 3) no of vanishing

moments

$$m_k = \int t^k \psi(t)\, dt.$$

If $m_0 = m_1 = m_2 = \ldots = m_{p-1} = 0$, we say $\psi(t)$ has vanishing moments. The number of vanishing moments of a wavelet analysis represents the order of a wavelet transform. According to the Strang-Fix conditions, the error for an orthogonal wavelet approximation at scale $a = 2^{-i}$ globally decays as a^L...L where is the order of the transform. In other words, a wavelet transform with higher order will result in better signal approximations [2].

Scaling Function:-

The wavelet function $\psi(t)$ and the scaling function $\varphi(t)$ define a wavelet. The scaling function is primarily responsible for improving the coverage of the wavelet spectrum. This could be difficult since time is inversely proportional to frequency. In other words, if we want to double the spectrum coverage of the wavelet in the time domain, we would have to sacrifice half of the bandwidth in the frequency domain. Instead of covering all the spectrum with an infinite number of levels, we use a finite combination of the scaling function to cover the spectrum. As a result, the number of wavelets required to cover the entire spectrum is greatly reduced [28], [30].

Scale Factor:-

The scale factor either dilates or compresses a signal. When the scale factor is relatively low, the signal is more contracted which in turn results in a more detailed resulting graph. However, the drawback is that low scale factor does not last for the

entire duration of the signal. On the other hand, when the scale factor is high, the signal is stretched out which means that the resulting graph will be presented in less detail. Nevertheless, it usually lasts the entire duration of the signal.

Several different families of wavelets
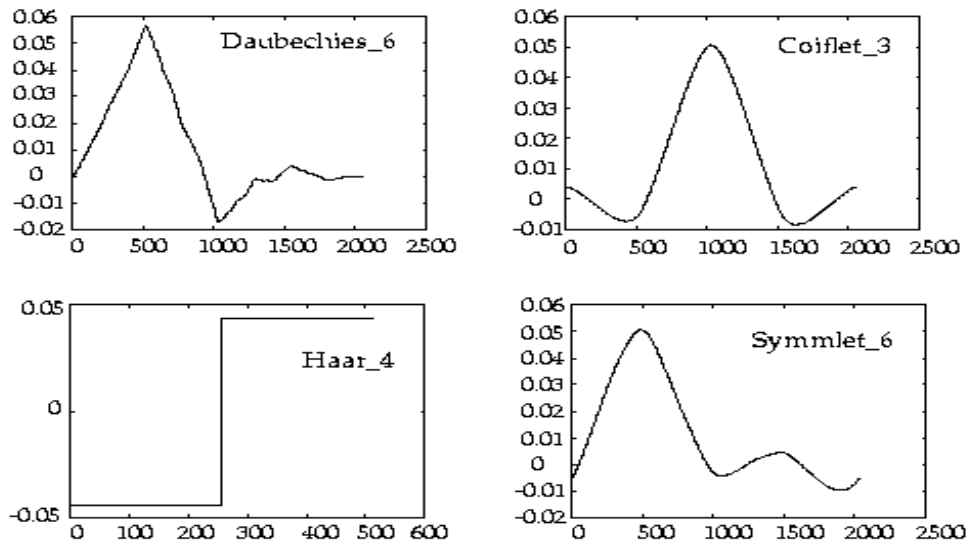
4.4.2. Discrete Wavelet Transfor (DWT):-

The DWT is an implementation of the wavelet transform using a discrete set of the wavelet scales and translation obeying some defined rules. For practical computations, it is necessary to discretize the wavelet transform. The scale parameter(s) is (are) discretized on alogarithmic grid. The translation parameter (t) is then discretized with respect to the scale parameter, i.e. sampling is done on the dyadic (as the base of the logarithm is usually chosen as two) sampling grid. The discretized scale and translation parameters are given by, s $= 2^{-m}$ and t = n 2^{-m} ,where m, n $\in$ Z , the set of all integers. Thus, the family of wavelet functions is represented in

$$\psi_{jk}(t) = \sqrt{2^{-j}}\,\psi\left(2^{-j}t - k\right) \quad j,k \in Z \qquad \text{(4.11)}$$

Forward DWT:
$$a_{jk} = \sum_{t} f(t)\psi^{*}{}_{jk}(t)$$

$$\text{......... (4.12)}$$

Inverse DWT:
$$f(t) = \sum_k \sum_j a_{jk} \psi_{jk}(t)$$
………(4.13)

The Discrete Wavelet Transform (DWT), which is a discrete time version of the CWT, is implemented by a filter bank that decomposes the signal using successive low pass and high pass filtering operations.

The DWT further has various other types of wavelet transforms like the Haar wavelets, Daubechies wavelets, Dual Tree Complex wavelet transform, Newland transform, Mexican hat wavelet etc [2]. MATLAB has a wavelet toolbox which incorporates all these wavelets and we can select the one we would like to apply to the input signal. We have used the Debauchies and Coif wavelets for our ECG input signal, giving the best results.among all seven wavelet functions.

4.4.3. Thresholding:-

Thresholding is used in wavelet domain to smooth out or to remove some coefficients of wavelet transform sub signals of the measured signal. The noise content of the signal is reduced, effectively, under the non stationary environment.

Through the WT the signal description coefficients corresponding to the wavelet system used can be obtained. Within each level (or scale) the signal is decomposed in two parts: the detail, related with the high frequencies, and the approximation, containing the information of the low frequencies. This last part is processed in a similar way in the next level, and so on. In this way it is possible to decompose the signal information (according to the frequency bands) in the detail levels, allowing a multi resolution (or multi scale) analysis [31].

Each characteristic point is preferentially detected in the details of a scale (or scales) corresponding to the appropriated frequencies. Detection errors due to contamination noise can be avoided by performing the detection on the scales that do not correspond to the noise dominant frequencies.

Wavelet thresholding is the signal estimation technique that exploits the capabilities of signal de-noising. Thresholding method is categorized into two types such as hard

thresholding and soft thresholding. Performance of thresholding purely depends on the type of thresholding method and thresholding rule used for the given application. The hard threshold function tends to have bigger variance and it is unstable (sensitive even small changes in the signal). However, soft thresholding function ( ) is much stable than hard thresholding and it tends to have a bigger bias due to the shrinkage of larger wavelet coefficients [31]. In addition to these methods, the hyper-trim shrinkage with α - trim thresholding is proposed for signal de-noising. In general, most of the researchers have proved that, the soft thresholding method gives the best results with other methods on de- noising the ECG signal.

Signal Denoising using the DWT consists of the three successive procedures, namely, signal decomposition, thresholding of the DWT coefficients, and signal reconstruction. Firstly, we carry out the wavelet analysis of a noisy signal up to a chosen level N. Secondly, we perform thresholding of the detail coefficients from level 1 to N. Lastly, we synthesize the signal using the altered detail coefficients from level 1 to N and approximation coefficients of level N. However, it is generally impossible to remove all the noise without corrupting the signal [32].
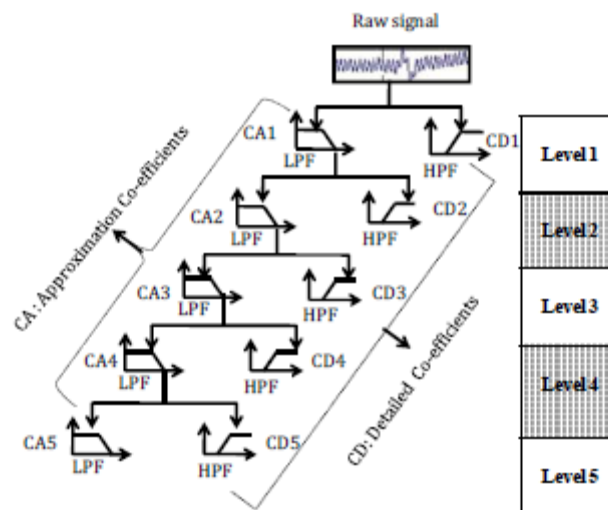

Fig 4.4 Filter Bank structure for implementing DWT [4]

4.4.4. Wavelet Filters:-

The time-frequency representation of DWT is performed by repeated filtering of the input signal with a pair of filters namely, low pass filter (LPF) and high pass filter (HPF), and its cut- off frequency is the middle of input signal frequency. The coefficient corresponding to the low pass filter is called as Approximation Coefficients (CA) and similarly, high pass filtered coefficients are called as Detailed Coefficients (CD) [32]. Furthermore, the CA is consequently divided into new approximation and detailed coefficients. This decomposition process is carried out until the required frequency response is achieved from the given input signal.

4.4.5. Wavelet Denoisig Algorithm:-

☐ Initially, decompose the input signal using DWT: Choose a wavelet and determine the decomposition level of a wavelet transform N, then implement N layers wavelet decomposition of signal S.

☐ Select the thresholding method and thresholding rule for quantization of wavelet coefficients. Apply the thresholding on each level of wavelet decomposition and this thresholding value removes the wavelet coefficients above the threshold value (soft thresholding).

☐ Finally, the denoised signals are reconstructed without affecting any features of signal interest. The reconstruction was done by performing the Inverse Discrete Wavelet Transform (IDWT) of various wavelet coefficients for each decomposition level. From the above three steps, the most critical is to select the proper threshold because, it directly reflects the quality of the de-noising.

4.4.6. Wavelet Thresholding on ECG signals:-

The ECG signals are visually inspected after the finishing the experiment and we found that, the signals are severely affected by using different sources of noises such as power line frequency, baseline wandering, and high frequency noises. However, it is impractical to remove the noises visually on definite duration of the acquired ECG signal and it consumes more time. Hence, robust signal processing techniques are

inevitable to remove such effects of noises from the ECG signals. In our project, we employed different types of wavelet thresholding methods to remove noises from the ECG signal. Previous researchers have used: "db1", "coif1" and "sym1" wavelet function for genetic algorithm based denoising in ECG signal [33]. I used the SEVEN wavelet functions ("db1", "coif1", "rbio1.1" ,"dmey" ,"bior1.1" ,"haar" and "sym1") for our de-noising. The soft thresholding method investigated with four different thresholding level to analyze the denoising performance of ECG signals. Based on the literature, all the noises are having certain frequency characteristics and ranges are: power line noise (50Hz or60Hz), baseline wander (>1Hz), and high frequency noises (>100). Therefore, the effect of noises in the frequency spectrum of acquired ECG lies in between (0-500) Hz [33].

After having collected the data for analysis and processing, a proper platform to perform the processing was to be chosen. After contemplating over all the options, MATLAB was chosen as the most appropriate software for this job.After generating the plot of the input signal in MATLAB, the next step is to de-noise the signal and make it completely noise free. After the literature survey, we decided on applying the wavelet transform as it was found out to be the most efficient method for de-noising of ECG signals. MATLAB provides toolboxes for various functions and it has a special toolbox for wavelet transforms. This toolbox enables the user to choose the desired wavelets, their levels and the threshold method. Hence, the customized wavelet transform can be performed easily using this toolbox. We have used the SEVEN wavelet functions ("db1", "coif1","rbio1.1" ,"dmey" ,"bior1.1" ,"haar" and "sym1") for level 4. Standard wavelet families, including Daubechies wavelet filters, complex Morlet and Gaussian, real reverse biorthogonal, and discrete Meyer. Using the toolbox we generated the code for the required wavelet transforms and used the generated code for denoising the signals. Also percentage denoising is calculated keeping into account the noise in the original signal and the noise in the denoised signal.

4.4.7. <u>Wavelet Toolbox</u>:-

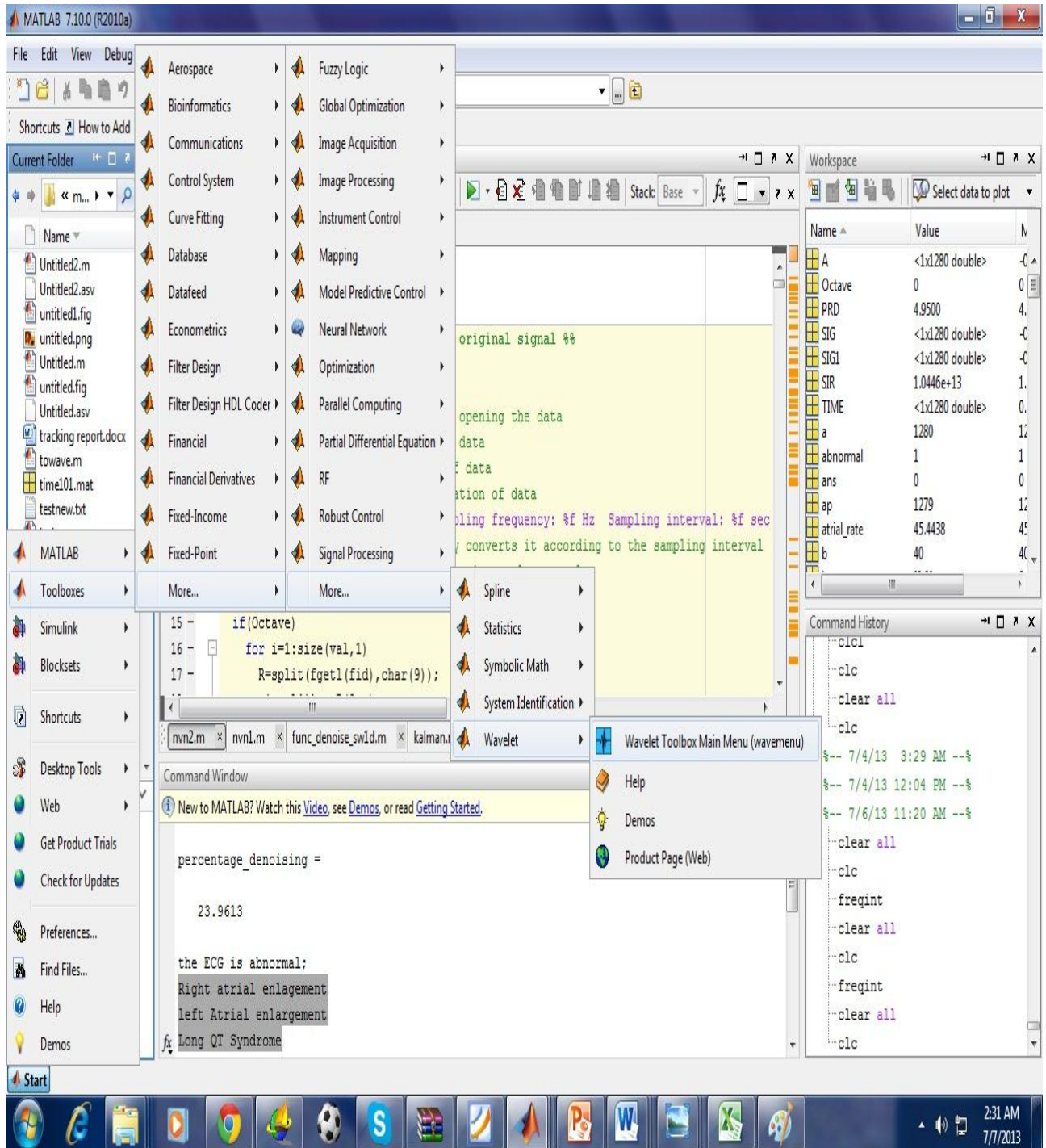Using The Wavelet Toolbox For De-Noising Of Input Ecg Signal

Step 1 : Open The Ecg Toolbox From The Matlab .

Step 2.: Choose The Swt De-Noisinng One Dimensional.

Step3: Choose The wavelet and decompose the ecg signal in particular level and then click on denoised signal as shown in below:
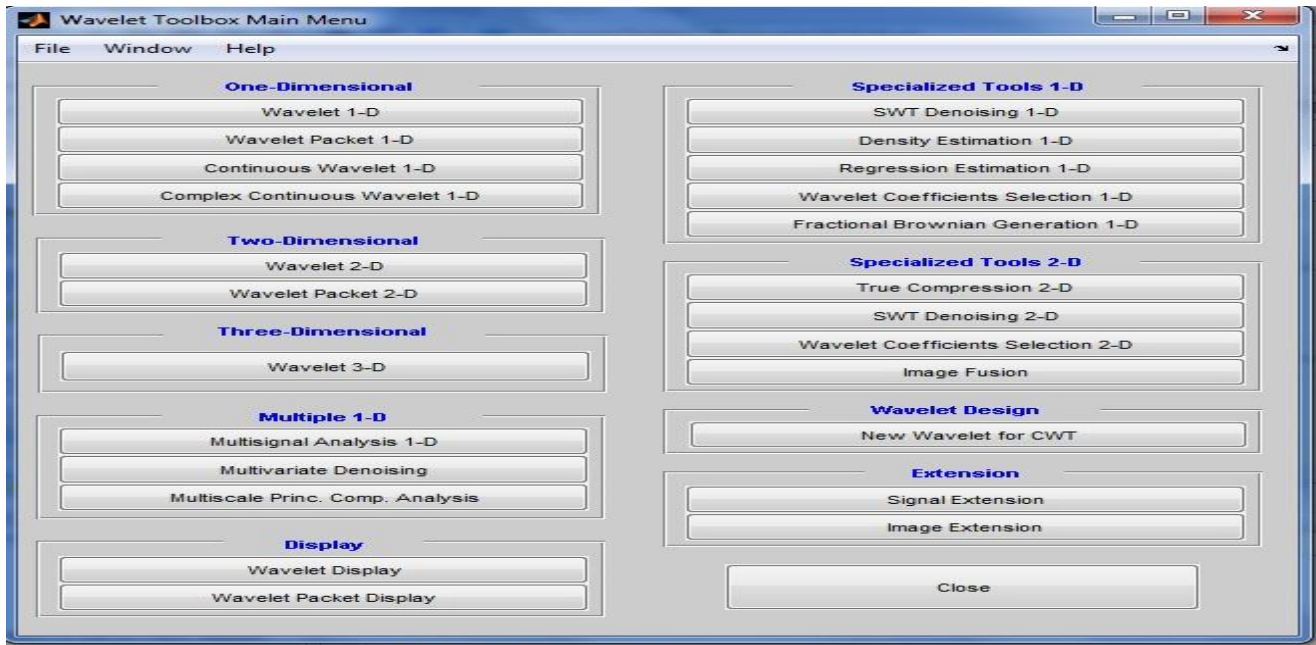
Figure 4.5 Starting Window For Wavelet Toolbox

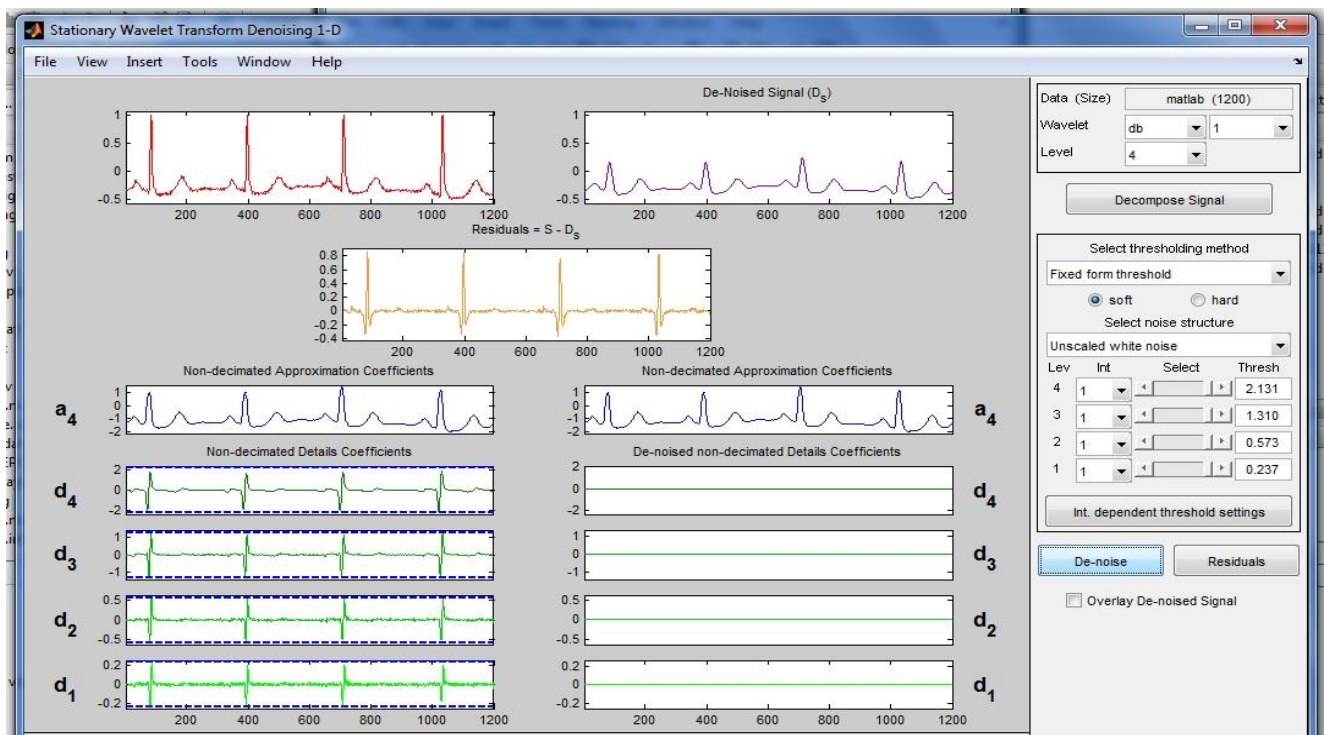Figure 4.6 Select SWT Denoising For ECG

Fig 4.7 Wavelet toolbox in MATLAB

After the input signal is made noise free, a smooth ECG signal is obtained and the peaks can be distinguished conspicuously. For detecting whether the ECG graph is normal or abnormal and further detecting the disease if abnormal, we need to have information about the peaks (P,Q,R,S and T). Also, the intervals would also be known if the peaks were detected. Hence, an algorithm was made to find the peaks, wherein we started with the top most peak, R- peak and then moved towards the left (for P and Q peaks) and right (for S and T peaks). Hence, this way all the peaks were detected. A code was written on the basis of this algorithm by using the most basic functions like the "for" loops and the "if" statements. The technique of **difference equations** was used to detect the peaks. As the peaks were detected, we could also get information about inverted or missing peaks, taller than normal peaks, intervals between peaks and other relevant information required for detecting the abnormality, if any present in the ECG signal. Hence, this was the most important part of the processing of ECG signal. This made way for the further work on detection and classification of diseases. And firstly we read all rule given below for normal and abnormal ecg.and then classification of diseases.

4.5. <u>The 10 rules for a normal ECG:-</u>

1.PR interval should be 120 to 200 milliseconds or 3 to 5 little squares.

2.The width of the QRS complex should not exceed 110 ms, less than 3 little squares.

3.The QRS complex should be dominantly upright in leads I and II.

4.QRS and T waves tend to have the same general direction in the limb leads

5.All waves are negative in lead aVR.

6.The R wave in the precordial leads must grow from V1 to at least V4.

7.The ST segment should start isoelectric except in V1 and V2 where it may be elevated.

8.The P waves should be upright in I, II, and V2 to V6.

9.There should be no Q wave or only a small q less than 0.04 seconds in width in I, II, V2 to V6.

10.The T wave must be upright in I, II, V2 to V6.[2]

4.6. The 10 rules for a abnormal ECG:-

1. Abnormally fast or irregular heart rhythms.

2. Abnormally slow heart rhythms.

3. Abnormal conduction of cardiac impulses, which may suggest underlying cardiac or metabolic disorders.

4. Evidence of the occurrence of a prior heart attack (myocardial infarction).

5. Evidence of an evolving, acute heart attack.

6. Evidence of an acute impairment to blood flow to the heart during an episode of a threatened heart attack (unstable angina) [1].

7. Adverse effects on the heart from various heart diseases or systemic diseases (such as high blood pressure, thyroid conditions, etc.).

8. Adverse effects on the heart from certain lung conditions (such as emphysema, pulmonary embolus (blood clots to lung), etc.).

9. Certain congenital heart abnormalities.

10. Evidence of abnormal blood electrolytes (potassium, calcium, magnesium).

11. Evidence of inflammation of the heart or its lining (myocarditis, pericarditis).

4.7. Detection of Heart Diseases:-

Interpretation & Analysis

ISCHAEMIA – impaired circulation to myocardium. T-wave inversion with or without S-T depression.

INJURY – S-T elevation = early sign of myocardial injury. Necrosis will occur unless immediate treatment is given.

INFARCT – death of a part of myocardium. Deep Q waves are a sign of this.[2]

Diagnostic criteria for AMI

Q wave duration of more than 0.04 seconds

Q wave depth of more than 25% of ensuing r wave

ST elevation in leads facing infarct (or depression in opposite leads)

Deep T wave inversion overlying and adjacent to infarct. Cardiac arrhythmias[2].

Basic Infarct Territories
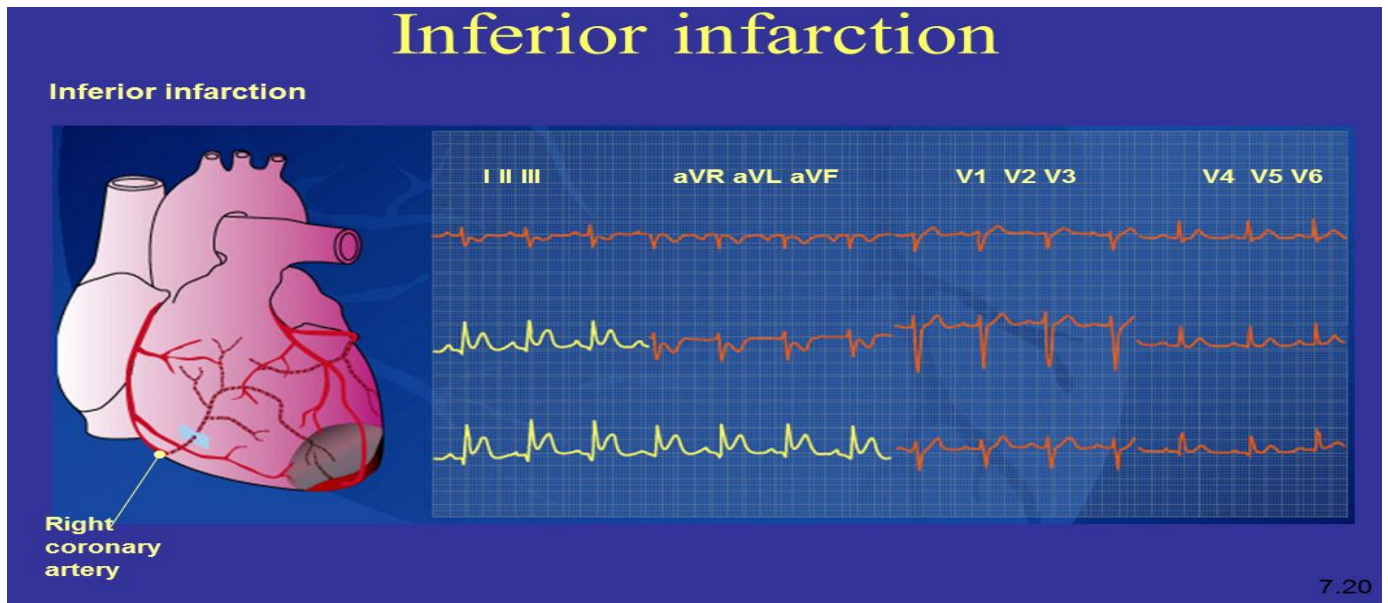
Figure 4.8   The Inferior Infarction Shown Abnormal Ecg Signal

Figure 4.8   The lateral infarction shown abnormal ecg signal

Figure 4.9   The Anterior infarction shown abnormal ecg signal

The ECG records the electrical activity of the heart, where each heart beat is displayed as a series of electrical waves characterized by peaks and valleys. Any ECG gives two kinds of information. One, the duration of the electrical wave crossing the heart which in turn decides whether the electrical activity is normal or slow or irregular and the second is the amount of electrical activity passing through the heart muscle which enables to find whether the parts of the heart are too large or overworked.

Normally, the frequency range of an ECG signal is of 0.05–100 Hz and its dynamic range – of

1–10 mV [37]. The ECG signal is characterized by five peaks and valleys labelled by the letters P, Q, R, S, T. In some cases we also use another peak called U. The performance of ECG analyzing system depends mainly on the accurate and reliable detection of the QRS complex, as well as T-and P-waves. The P-wave represents the activation of the upper chambers of the heart, the atria, while the QRS complex and T-wave represent the excitation of the ventricles or the lower chamber of the heart. The detection of the QRS complex is the most important task in automatic ECG signal analysis. Once the QRS complex has been identified a more detailed examination of ECG signal including the heart rate, the ST segment etc. can be performed [38].

In the normal sinus rhythm (normal state of the heart) the P-R interval is in the range of 0.12 to 0.2 seconds. The QRS interval is from 0.04 to 0.12 seconds. The Q-T interval is less than 0.42 seconds and the normal rate of the heart is from 60 to 100 beats per minute. So, from the recorded shape of the ECG, we can say whether the heart activity is normal or abnormal [37].

The electrocardiogram is a graphic recording or display of the time variant voltages produced by the myocardium during the cardiac cycle. The P-, QRS-and T-waves reflect the

rhythmic electrical depolarization and repolarization of the myocardium associated with the contractions of the atria and ventricles. This ECG is used clinically in diagnosing various abnormalities and conditions associated with the heart. The following are the normal values of the amplitude and duration of the peaks and intervals respectively.

Amplitude:

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

Duration:
P-R interval: 0.12 to 0.20 s
Q-T interval: 0.35 to 0.44 s

S-T interval: 0.05 to 0.15 s

P-wave interval: 0.11 s

QRS interval: 0.04 - 0.09s

The normal value of heart beat lies in the range of 60 to 100 beats/minute. A slower rate than this is called bradycardia (Slow heart) and a higher rate is called tachycardia (Fast heart) [1]. If the cycles are not evenly spaced, an arrhythmia may be indicated. If the P-R interval is greater than 0.2 seconds, it may suggest blockage of the AV node .Certain disorders, involving heart valves cannot be diagnosed from ECG. Other diagnostic techniques such as angiography and echocardiography can provide information not available in ECG.Each action potential in the heart originates near the top of the right atrium at a point called the pacemaker or sinoatrial (SA) node.

The wave generated by action potential, terminates at a point near the center of the heart, called the atrioventricular (AV) node.

The horizontal segment of this waveform preceding the P-wave is designated as the baseline or the isopotential line. The P-wave represents depolarization of the atrial musculature. The QRS complex is the combined result of the repolarization of the atria and depolarization of the ventricles, which occur almost simultaneously.

The T-wave is the wave of ventricular repolarization, where as the U-wave, if present is generally believed to be the result of after potentials in the ventricular muscle. So, the duration amplitude and morphology of the QRS complex is useful in diagnosing cardiac arrhythmias, conduction abnormalities, ventricular hypertrophy, myocardial infection and other disease states.

Chapter 5
Results

Step wise results for the ECG signal. After generating the plot of the input signal in MATLAB, the next step is to de-noise the signal and make it completely noise free. After the literature survey, we decided on applying the wavelet transform as it was found out to be the most efficient method for de-noising of ECG signals. MATLAB provides toolboxes for various functions and it has a special toolbox for wavelet transforms. This toolbox enables the user to choose the desired wavelets, their levels and the threshold method. After having collected all the data required for detection of the diseases, we started making the step by step algorithms and writing the codes. The very step was generating the input signal in MATLAB. For this a code was used and it gave the input signal with noise as shown below in given figure.
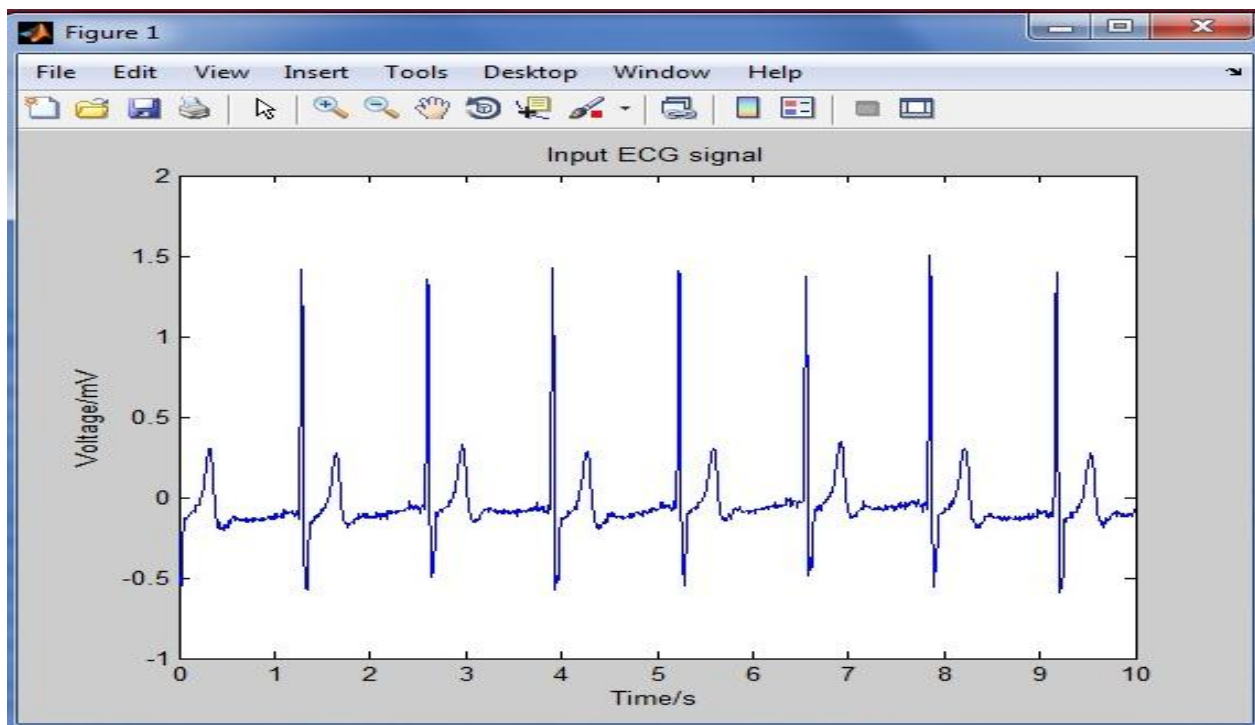
Figure5.1: original ECG signal with noise

5.1. Results for normal signals(De-Noised Signal):-

As seen above , this original signal has a lot of noise and the peaks are not clearly visible. ForThis reason, denoising is done and the code for de-noising is applied on this signal. SEVEN wavelet functions ("db1","coif1","rbio1.1","dmey","bior1.1" ,"haar"and "sym1") and four different thresholding levels are used to de-noise the noise in ECG signals. Can be seen in the figures given below:
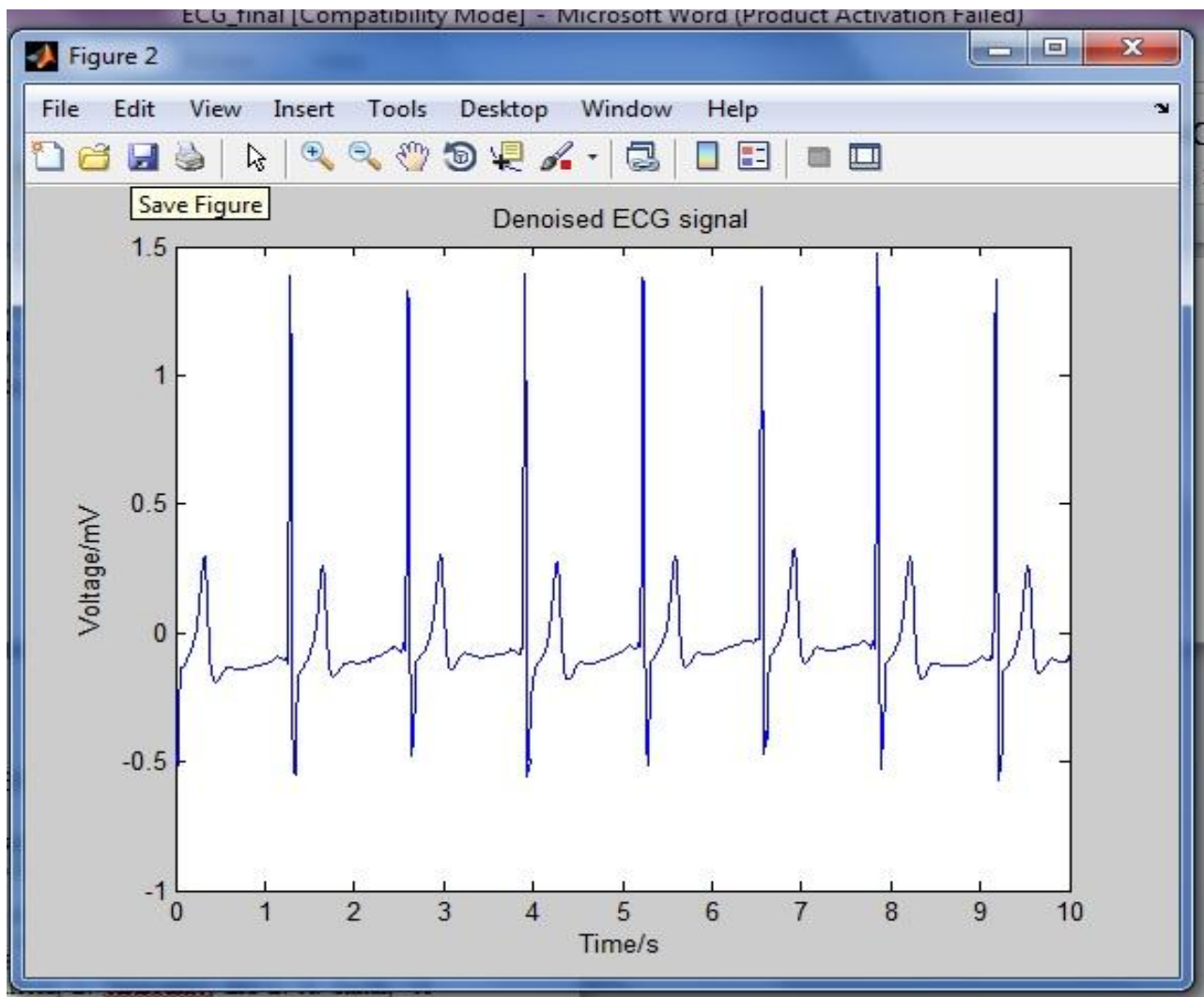
Figure5.2: De-Noised Signal

5.2. <u>De-Noised Signal Superimposed On Original Signal:-</u>
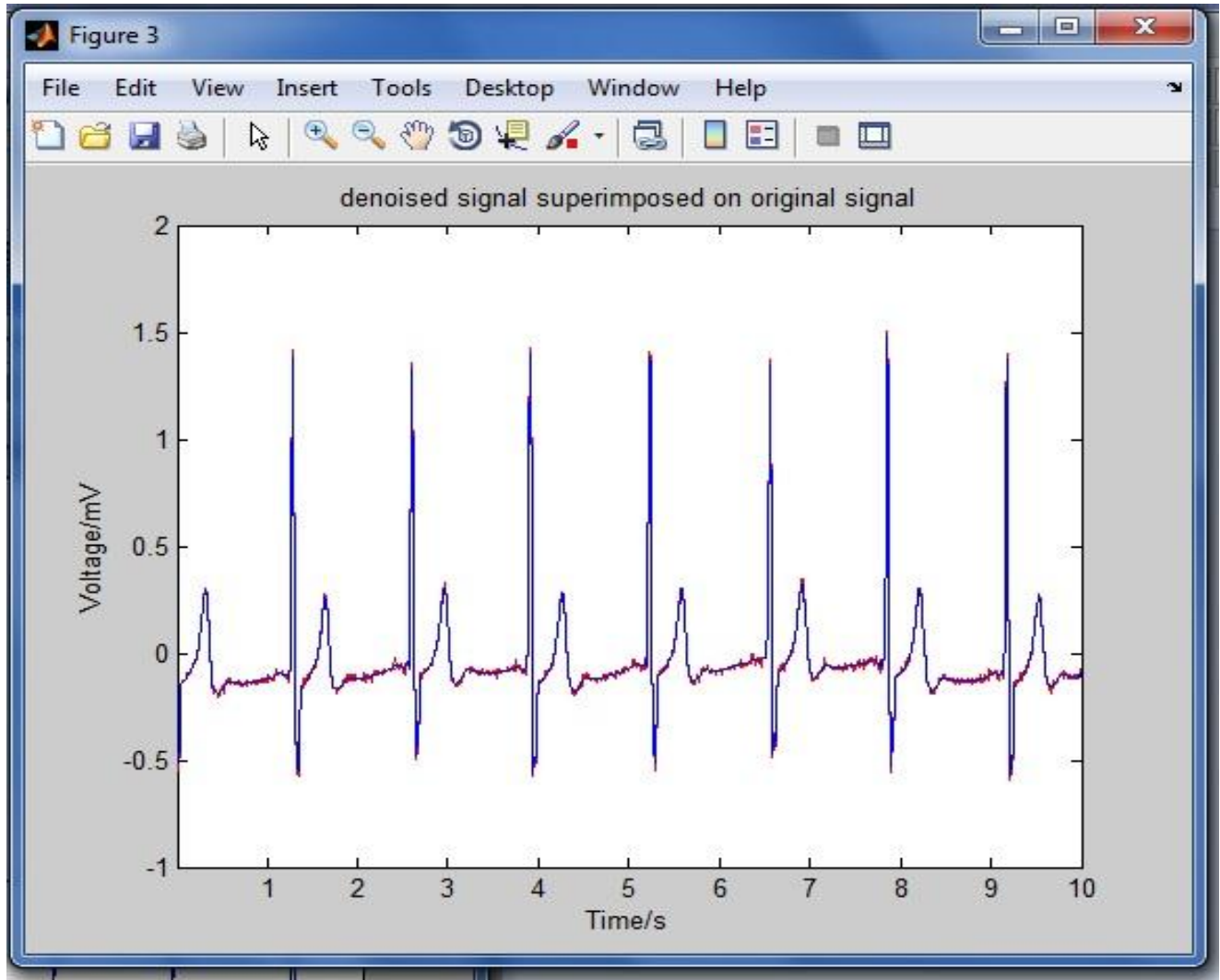
Figure5.3 : De-Noised Signal Superimposed On Original ECG Signal

The percentage denoising was also calculated from the signal representing the amount of noise removed from the signal.These were the results obtained for de-noising of the original ECG signal.hence, first stage of the process was successfully completed. After this, the next job was to remove the baseline wandering and then peak detection. After detecting the peak, it should be detected whether the signal is normal and abnormal and if abnormal, then the name of the diseases should be displayed as output.

5.3 **Feature Extraction(peaks) of Denoised Ecg Signal :-**

E
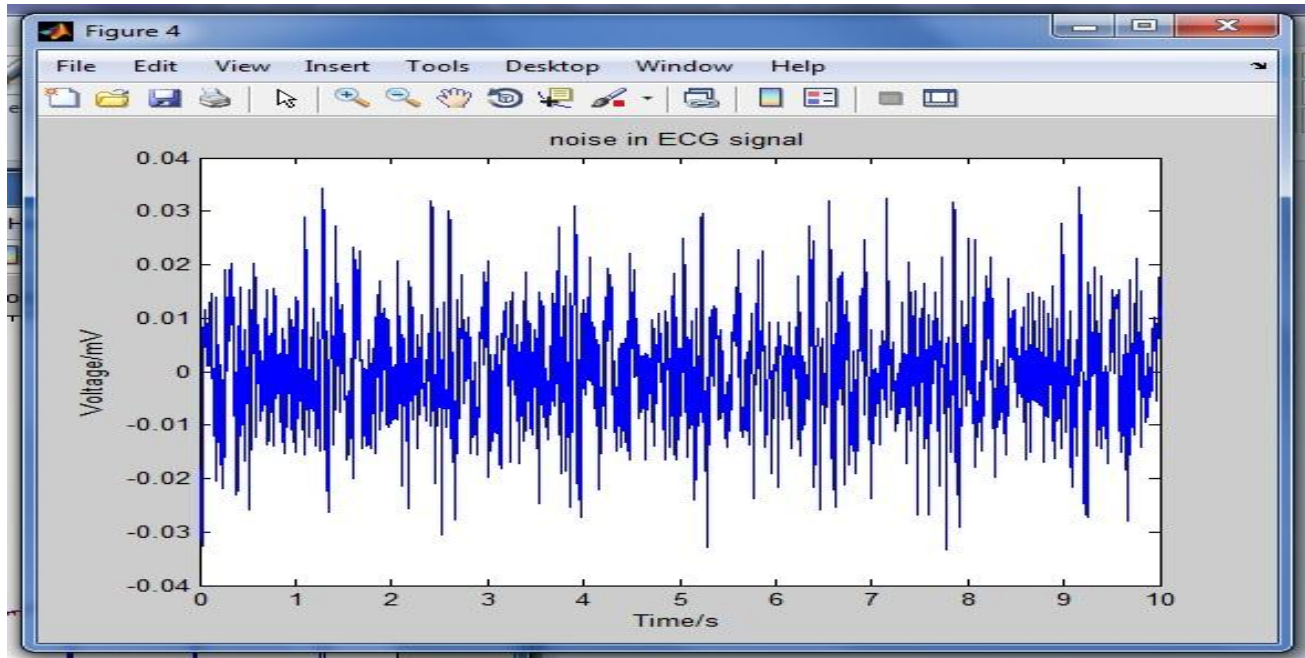
Figure5.4: Noised Ecg Signal

The classification of ECG signal into normal and abnormal ECG signal requires the knowledge of three parameters. These are the RR interval(Heart Rate), the PR interval and the QRS duration. For determining these parameters a first set of features is obtained from the original ECG signal. This set consists of the R peaks, the onset of P wave, the onset of QRS complex and j point.

The R peaks have been obtained previously and have been used to segment the ECG into different beats. After segmentation into beats each beat is analysed separately to extract the features contained in it. We search the segment behind the R peaks in every beat to obtain the Q peak as the point where the slope changes from positive to negative as we move away from the R peak. $Q(j) = (R(j)-i+1)|_{y(R(j)-i)>=(y(R(j)-i+1))}$,   (5.1)

where, $Q(j)$ is the Q peak in the jth beat segment and i is the distance from the R peak. From this, the onset of the QRS complex is calculated as the first inflexion point as we move away from the Q point towards the left. $QRS(j) = (Q(j)-i+1)|_{y(Q(j)-i)<=(y(Q(j)-i+1))}$,   (5.2)

where, $QRS(j)$ is the onset of the QRS complex in the jth beat segment and i is its distance from

the Q peak. For the onset of P waves we first calculate the P peaks by searching the area to the left of the Q peaks for a maximum. This is the P peak.

$$P(j) = (R(j) - i)|_{y(i)=max}, \qquad\qquad (5.3)$$
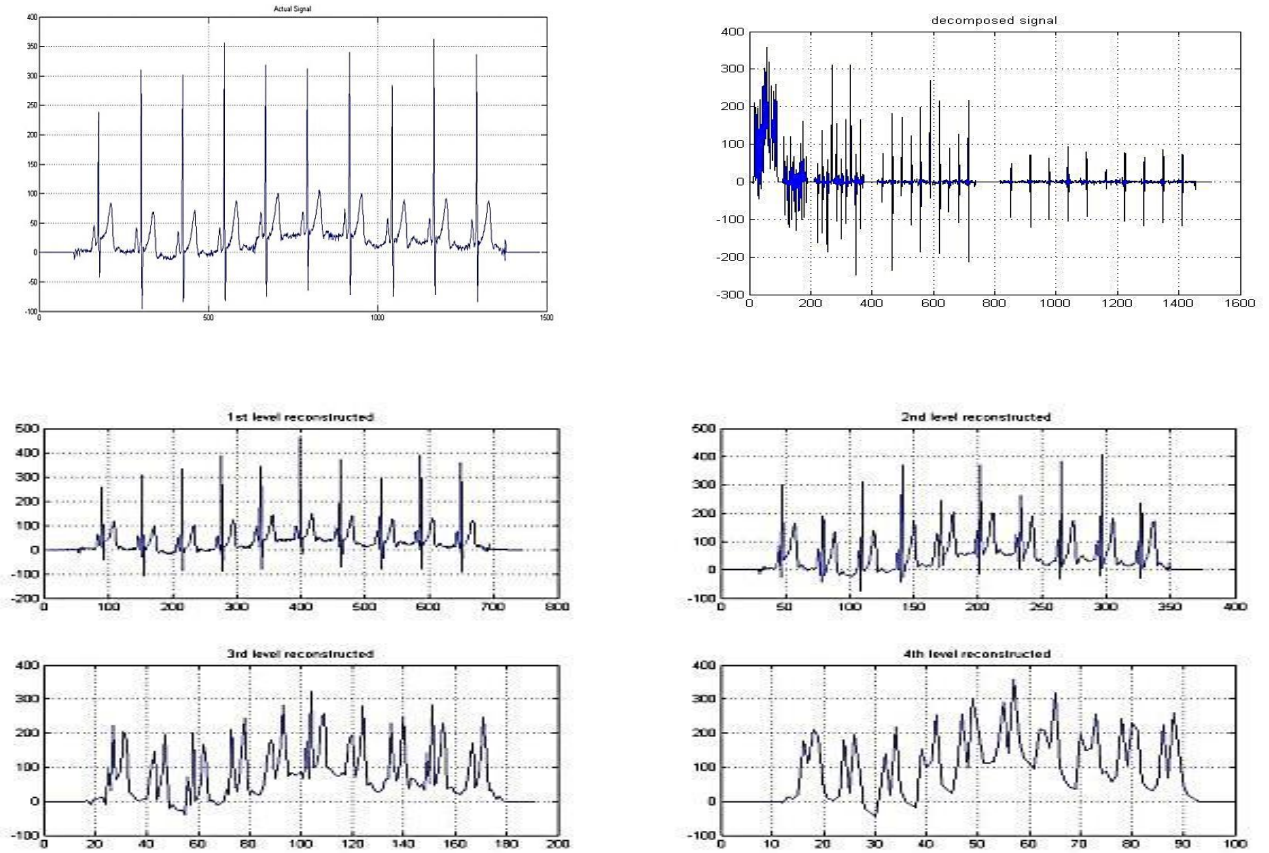
(c) Different level reconstructions
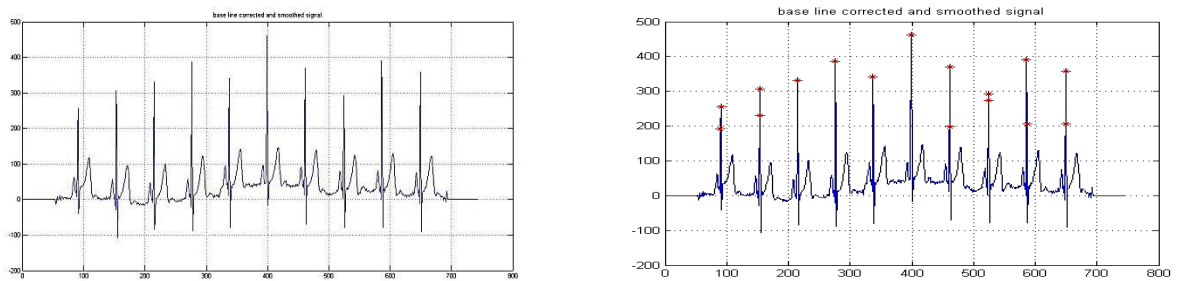
(d) smoothed signal

(e) signal value above threshold value

Figure 5.5 preprocessing of the Ecg signal

where, P(j) is P peak of the jth beat segment, i is an index and max is the maximum value of the signal to the left of the R peak. The P wave onset can now be calculated as,

$$PON(j) = (P(j)\text{-}i\text{+}1) \, |_{y(P(j)\text{-}i)>=(y(P(j)\text{-}i\text{+}1)} , \qquad (5.4)$$

where, PON(j) is the P onset of the jth beat segment and i is distance from P peak. The J point is hard to extract as the ST-T segment rises very sharply and hence the ST segment may not be easily separable. In order to find J point the S peak is first found out as follows,

$$S(j) = (R(j)\text{+}i)|_{(y(R(j)\text{+}i)<=(y(R(j)\text{+}i\text{+}1)} \qquad , \qquad (5.5)$$

where, S(j) is the S peak of the jth beat segment and i is the distance from R peak. Hence, it is calculated as the point after the R peak where slope changes from negative to positive. The T peak is now calculated as the point of maximum in the region after the R peak in the beat segment.

$$T(j) = (R(j) + i)|_{y(i) = max2} , \qquad (5.6)$$

where, T(j) gives the T peak of the jth beat segment, I is an index and max2 is the maximum value of the signal in the beat to the right of the R peak. The region between the S peak and T peak is now analysed for any slope change. First we analyse if the slope changes from positive to negative,

$$J(j)=(S(j)\text{+}i)|_{(y(S(j)\text{+}i)>((y(S(j)\text{+}i\text{+}1))\text{-}k))} , \qquad (5.7)$$

where, J(j) is the J point in the jth beat segment, I is its distance from the S peak and k is a constant equal to 0. If the J point and T point coincide we analyse the area between the S and T peaks again for the first inflexion point as we move away from S peak and towards T peak. For this case k = 1. If J point and T peak still coincide then we look for the point where slope decreases. For this purpose the
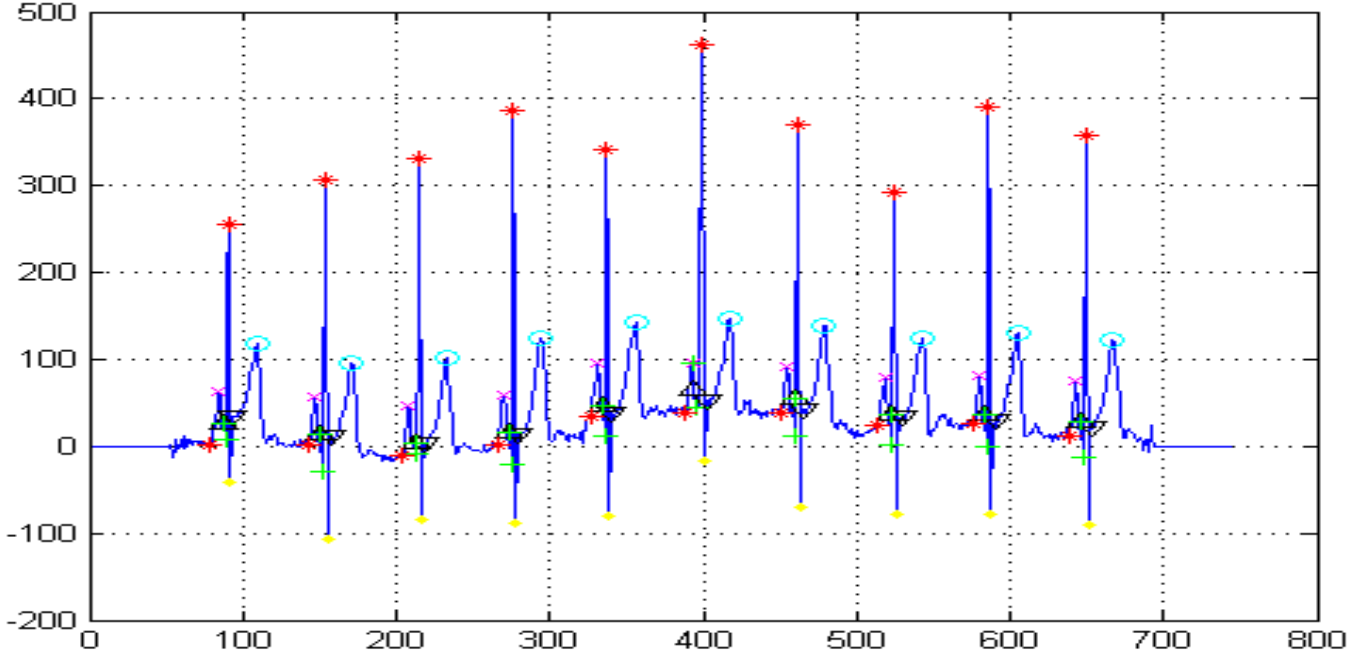
Figure.5.6 All the extracted features(P,Q,R,S,T,U).

value of variable k is increased till we find a J point not coinciding with T peak. All the extracted features are shown in Figure 5.6.

The primary basis for classification of the ECG signal by a physician is through the analysis of the rhythm of the ECG signal. Therefore the feature extraction scheme used in this paper takes into account three ECG durations, namely,

- The RR interval or Heartbeat of the patient is measured as the distance between two successive R peaks.
- The PR interval is measured as the length from the onset of the P wave to the onset of the QRS complex.
- The QRS complex width measured from the onset of the QRS complex to the j point.

Now the reduced feature set consists of these three features. These features are calculated as follows,

RR(i) = R(i+1) - R(i)   (5.8)

PR(i) = Q(i) - P(i)   (5.9)

QRS(i) = J(i) - Q(i)   (5.10)

here, i represents the index of the beat, R(i) represents the R peak in the ith beat, Q(i) represents the onset of the QRS complex in the ith beat, P(i) represents the onset of the P wave in the ith beat, J(i) represents the j point of the ith beat.

Constant K is designated the value of theRR interval that a normal person is expected to have. Constant L is similarly the value of the PR interval of a normal person and M is the QRS complex width of a normal person. The feature set is modified using these three constants to produce features A, B and C, where,

$$\text{Feature A} = \frac{RR(i)}{K} \qquad\qquad (5.11)$$

$$\text{Feature B} = \frac{PR(i)}{L} \qquad\qquad (5.12)$$

$$\text{Feature C} = \frac{QRS(i)}{M} \qquad\qquad (5.13)$$

The classification of the ECG signal as one belonging to a healthy or not healthy person is done on the basis of the three features extracted. The ECG signal is classified as normal if the following conditions are met,

- The mean feature A lies between 0.6 and 1.0.
- The mean feature B lies between 0.75 to 1.25.
- The mean feature C lies between 0.5 to 1.5.

When a signal does not satisfy all the above three conditions simultaneously it is classified as abnormal.The proposed algorithm in this thsis can be used for accurate and fast feature extraction from any ECG signal and for further classification into normal and abnormal signal. The ECG signal has been properly analysed an errors have been effectively minimized. The

baseline wander removal algorithm and subsequent segmentation into beats is very effective and lead to highly accurate feature extraction. The techniques used for feature extraction too are very efficient and show 98% accuracy. The original feature set was reduced to three features that were used for classification. The features and hence the classification is purely rhythm based. We have used a simple classifier but the features extracted are so distinct that they lead to highly accurate distinction between normal and abnormal ECG data abnormal.

After the detection of peaks and having all the information about the intervals too, the next step was to detect whether the signal is normal or abnormal and detect the disease if abnormal. For this purpose, a lot or research was required about the various diseases related to the heart that could be detected by interpreting the ECG signal.

After having collected all the data required for detection of the diseases, we started making the step by step algorithms and writing the codes. The very first step was generating the input signal in MATLAB. For this, a code was used and it gave the input signal with noise as shown above in the given figure. The results of the entire process are hereby displayed below for a normal ECG signal, without any disease.

Figure 5.7. Showing That The ECG Signal Is Normal And The Percentage Of Noise Present In Original Ecg Signal

5.4. Results For Abnormal Signals:-

The steps remain the same for abnormal signals too. The only difference is that the detection of the disease should be done accurately and the output should show display the name of the disease(s) after the program is run on the input signal.

Figure 5.8. Showing That The ECG Signal Is Abnormal And The Percentage Of Noise Present In Original Ecg Signal

Figure 5.9. Showing That The ECG Signal Is Abnormal And The Percentage Of Noise Present In Original Ecg Signal

Figure 5.10. Showing That The ECG Signal Is Abnormal And The Percentage Of Noise Present
In Original Ecg Signal
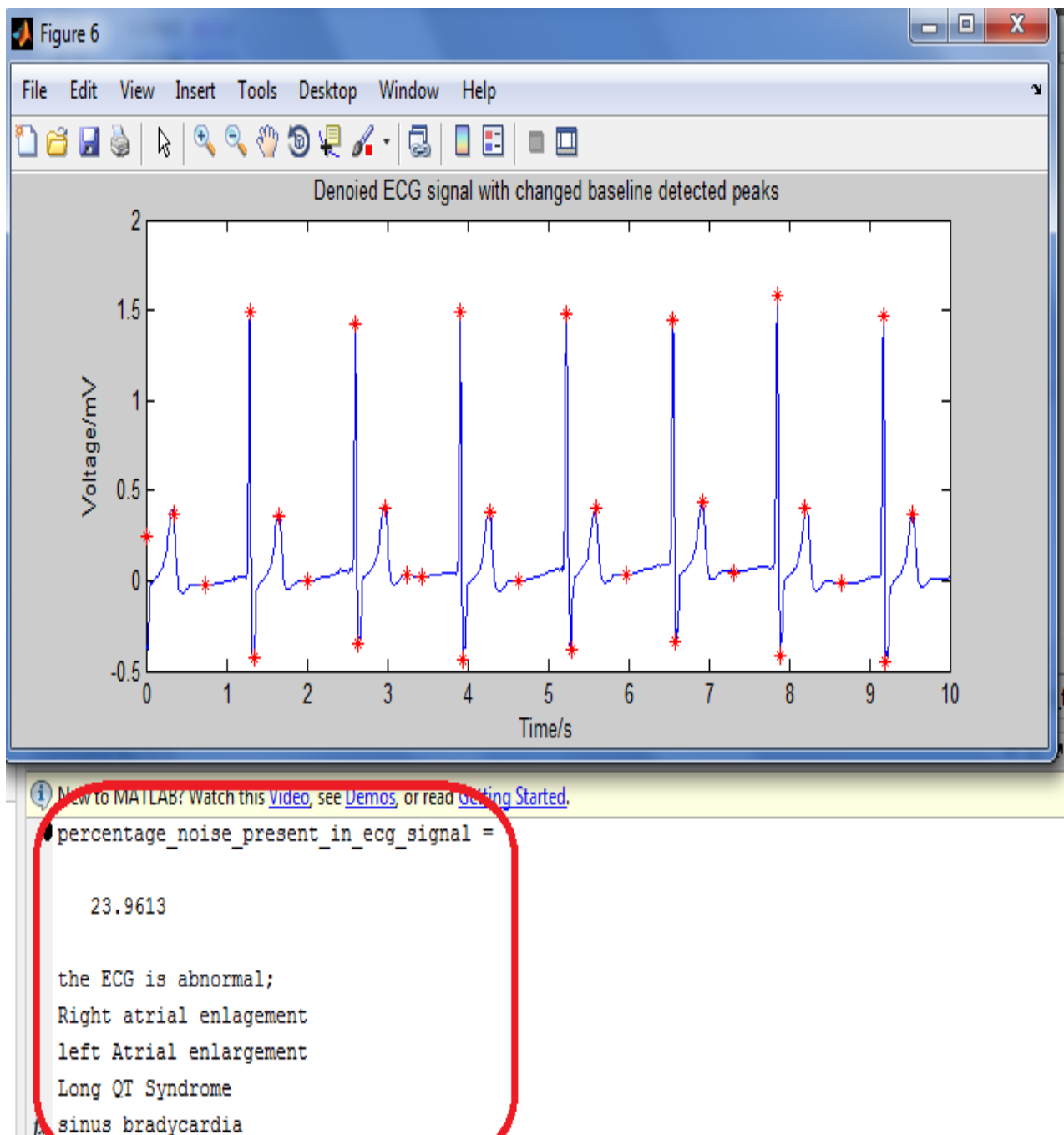
Figure 5.11. Showing That The ECG Signal Is Abnormal And The Percentage Of Noise Present In Original Ecg Signal
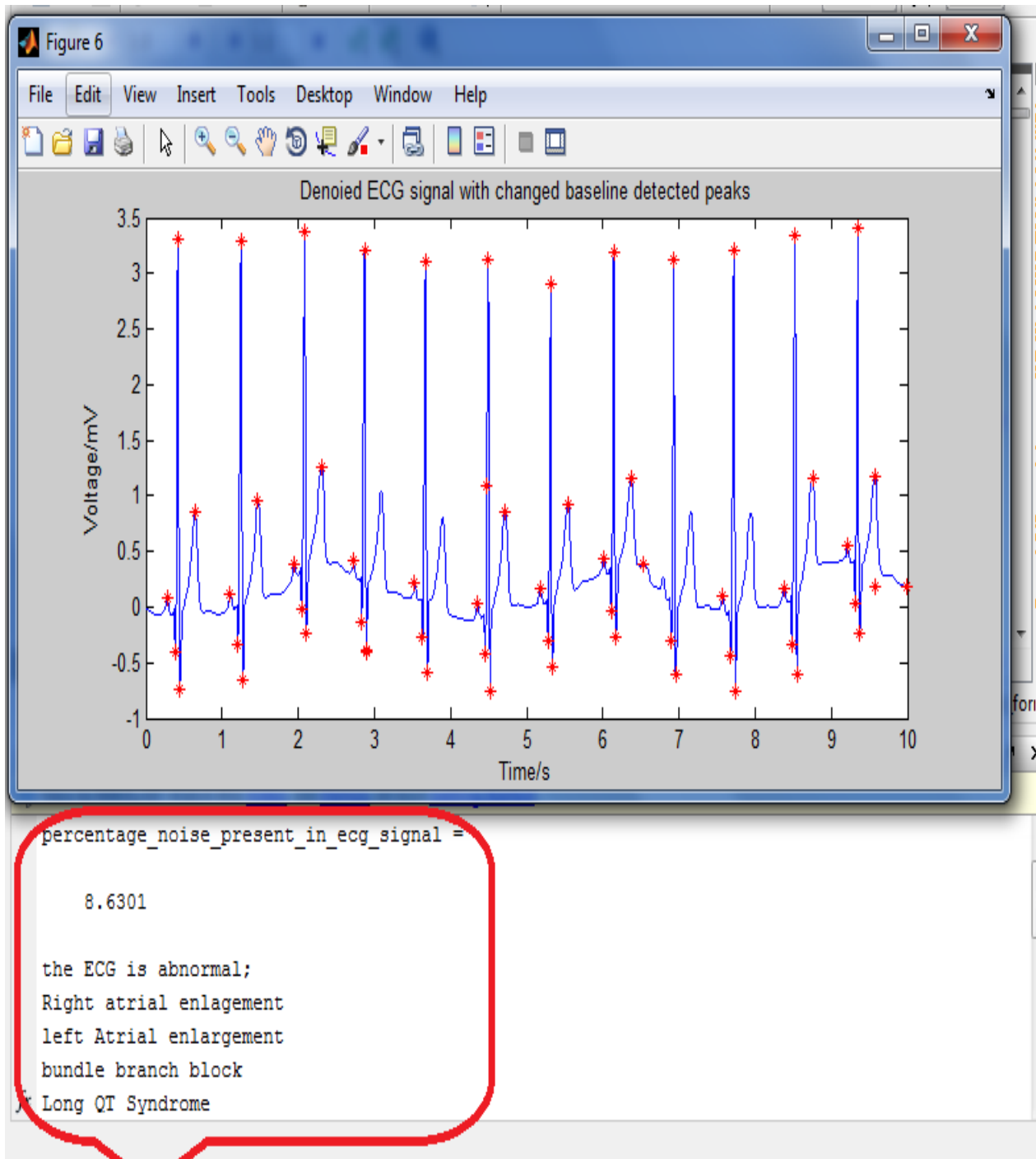
Figure 5.12. Showing That The ECG Signal Is Abnormal And The Percentage Of Noise Present In Original Ecg Signal
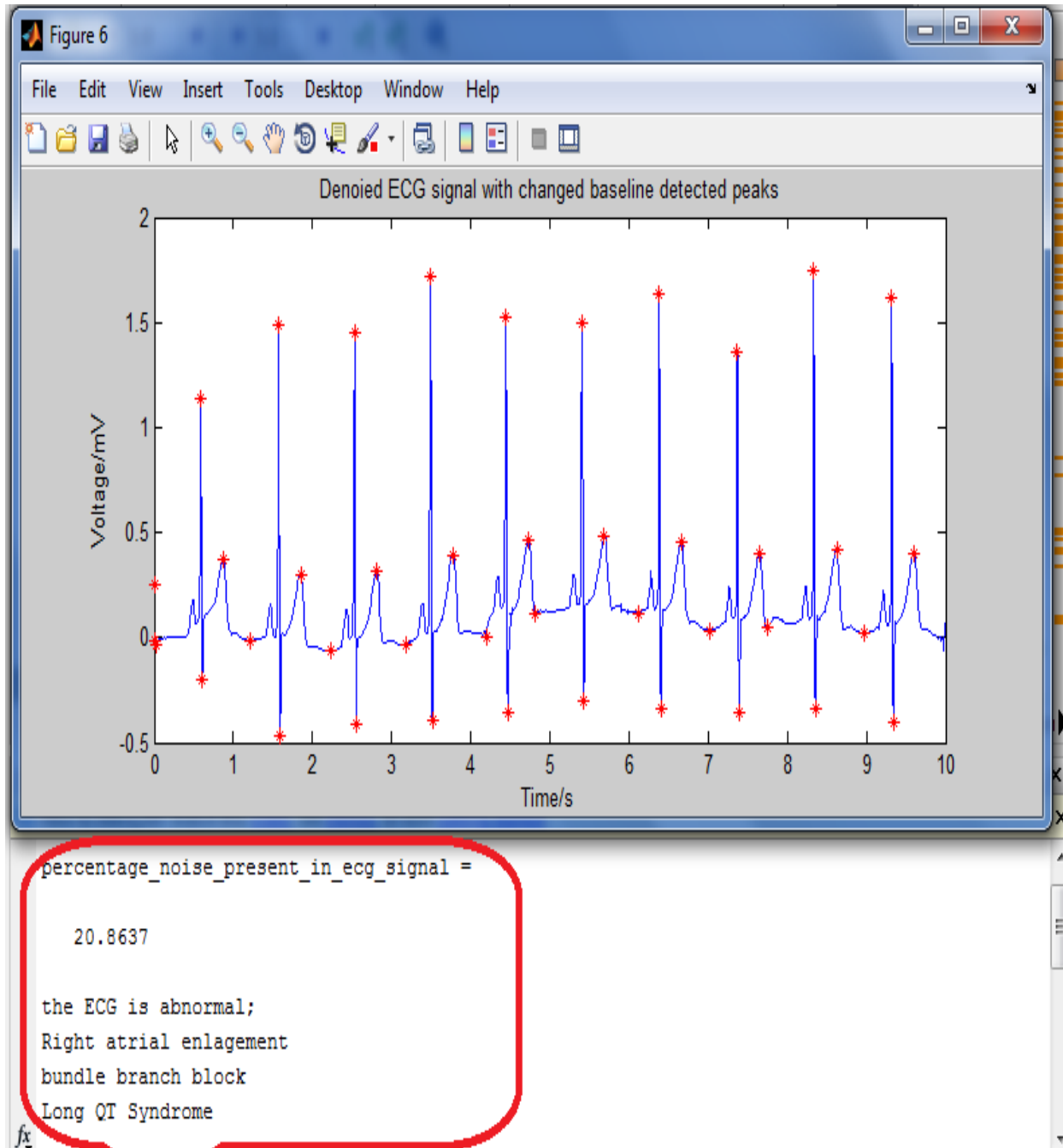
Figure 5.13. Showing That The ECG Signal Is Abnormal And The Percentage Of Noise Present In Original Ecg Signal

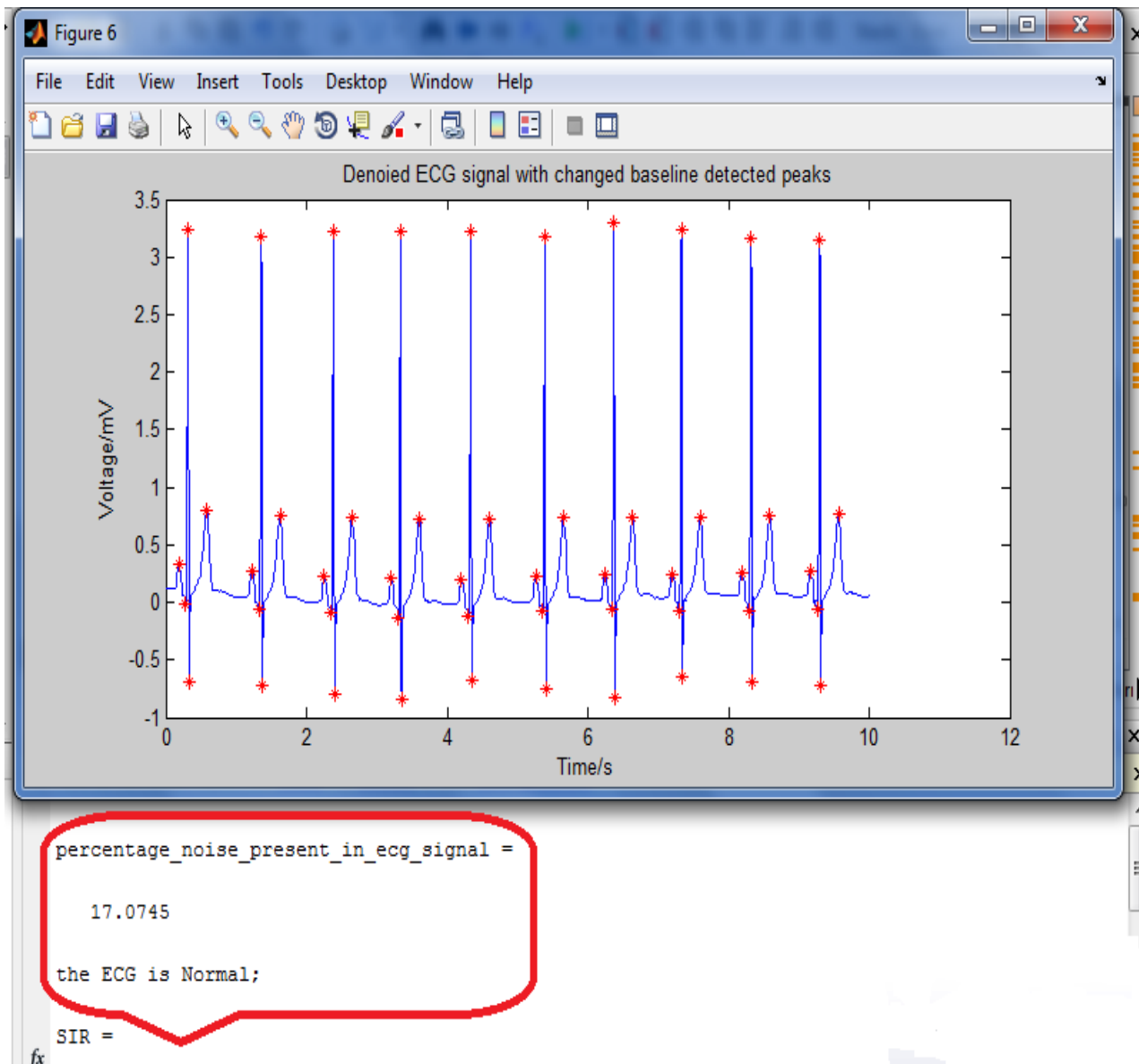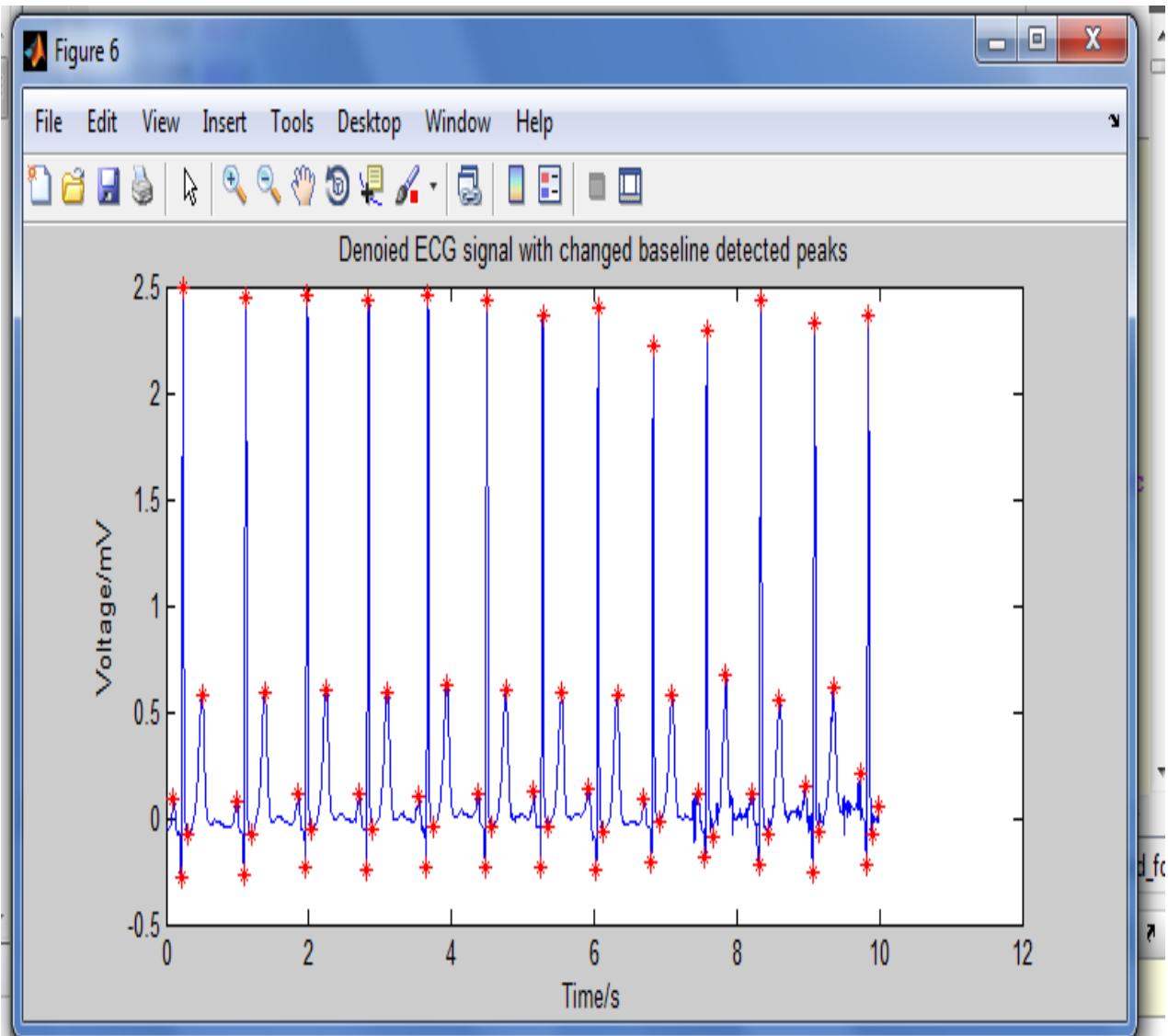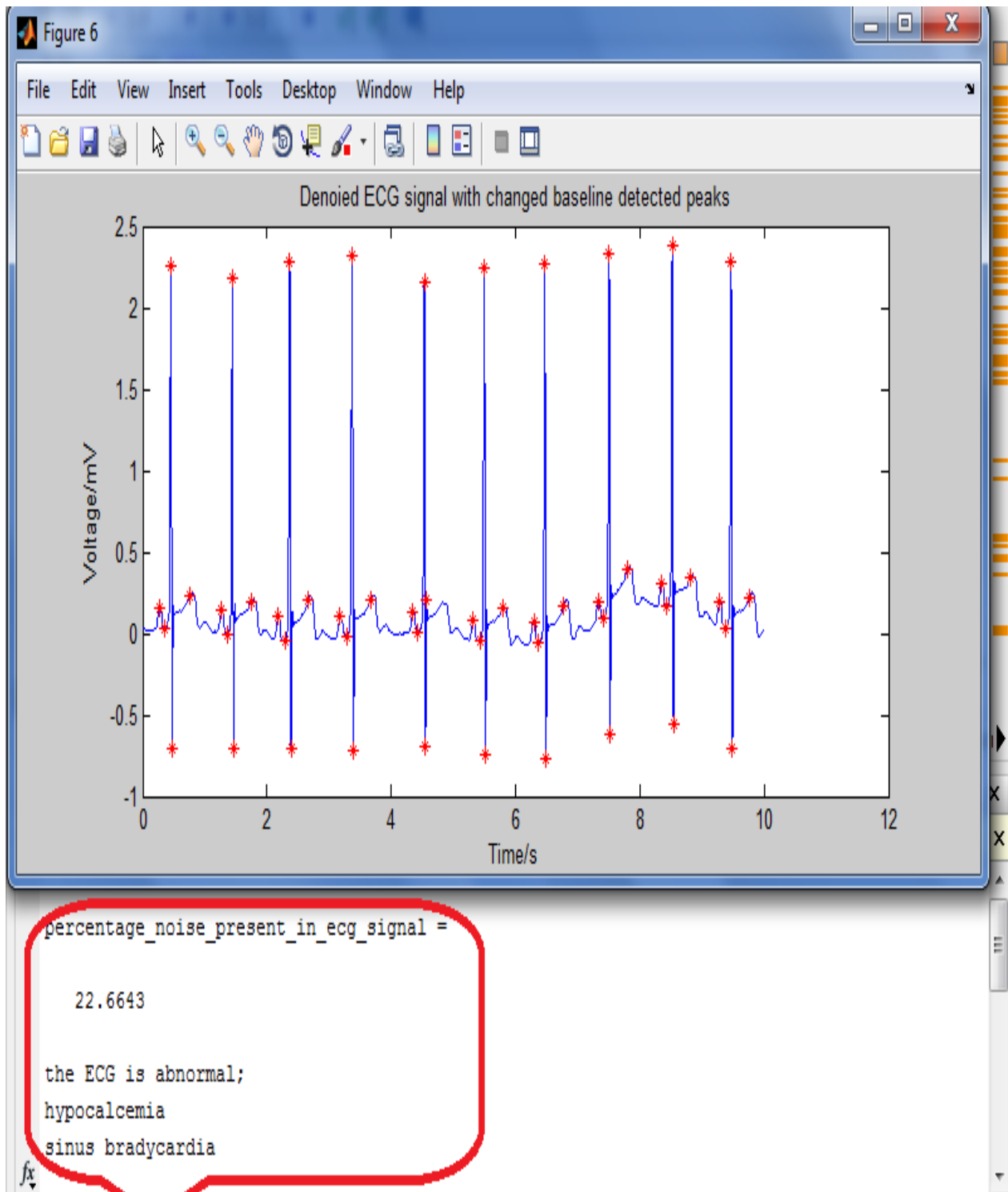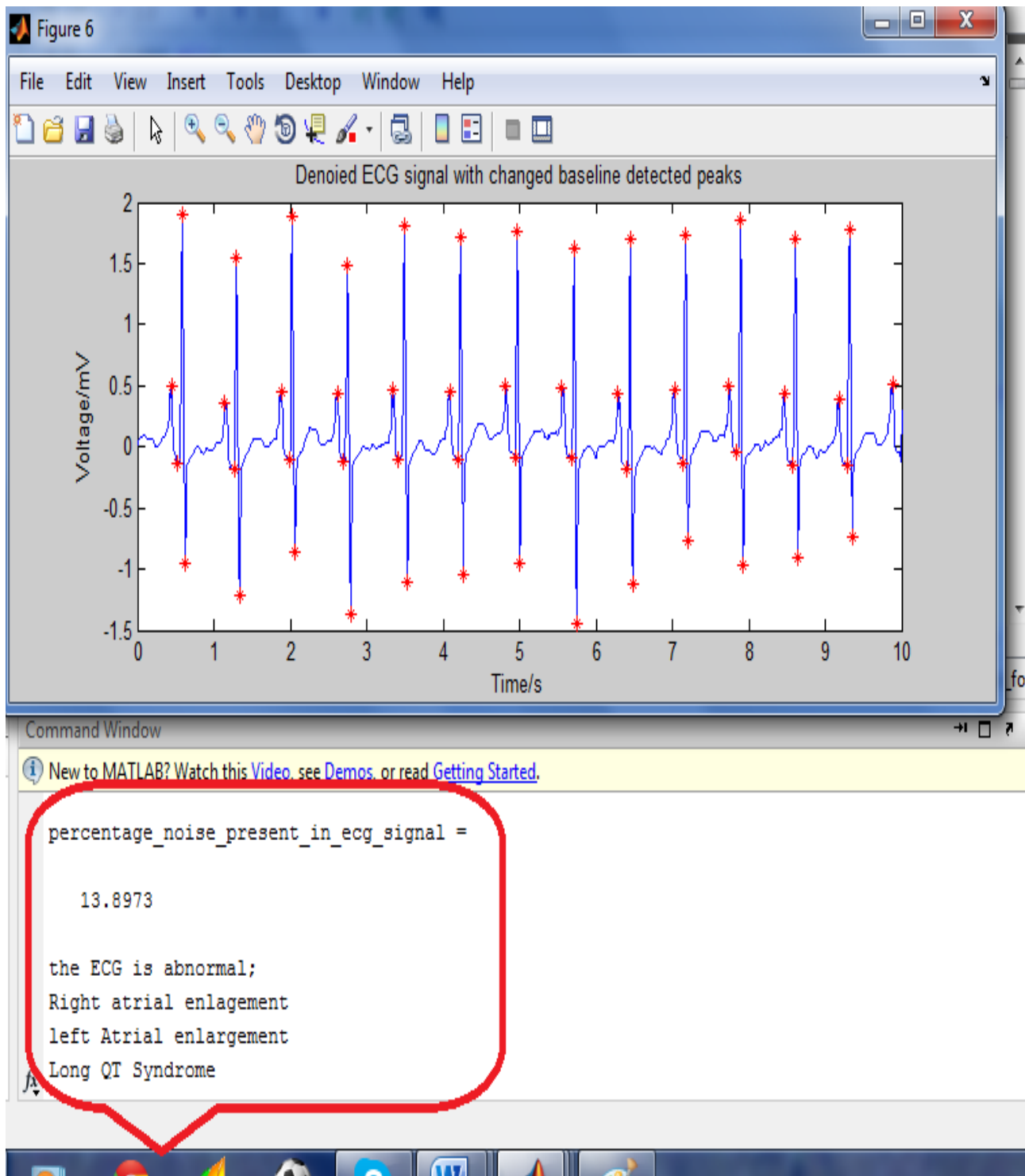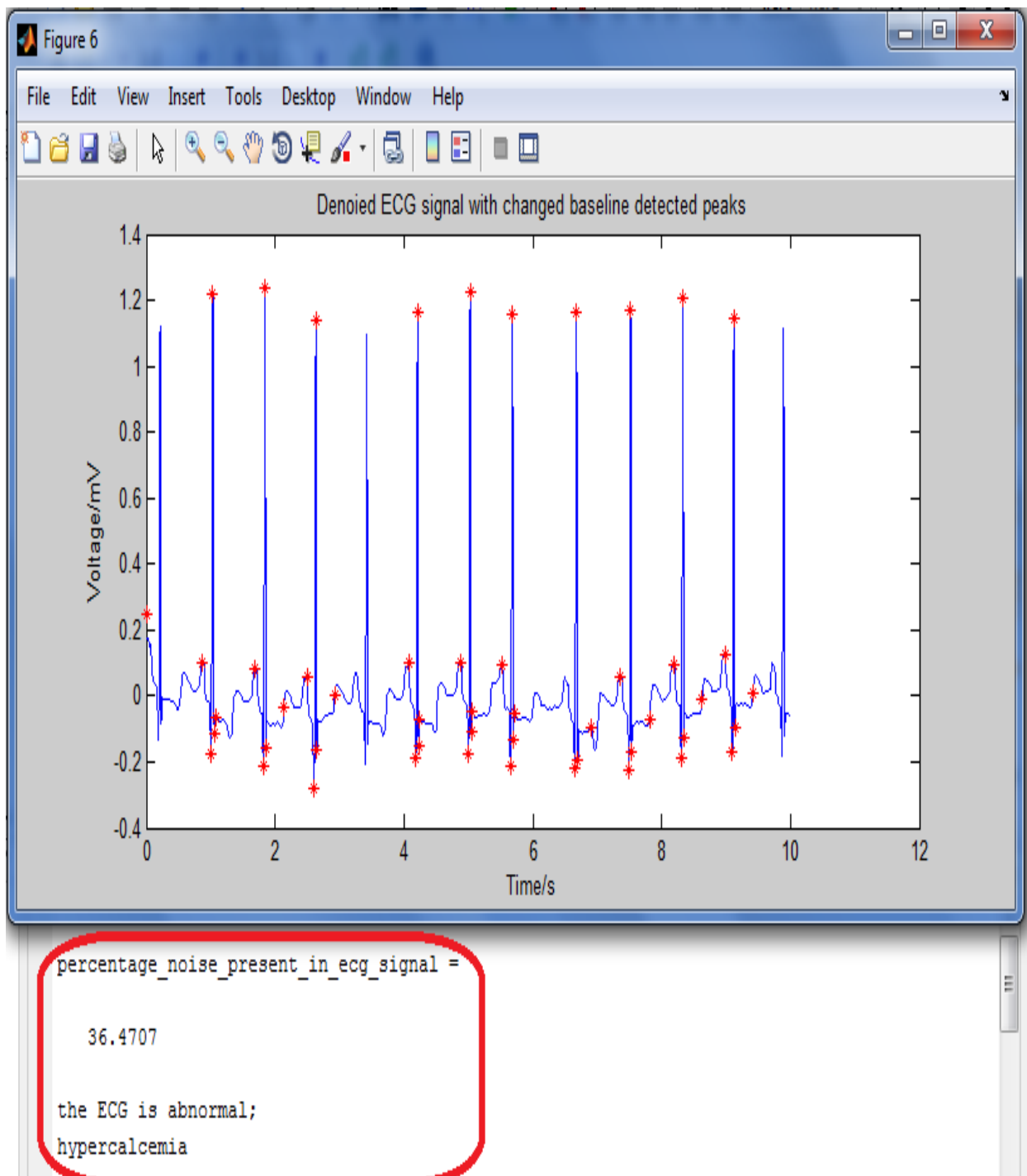Figure 5.14. Showing That The ECG Signal Is Abnormal And The Percentage Of Noise Present In Original Ecg Signal
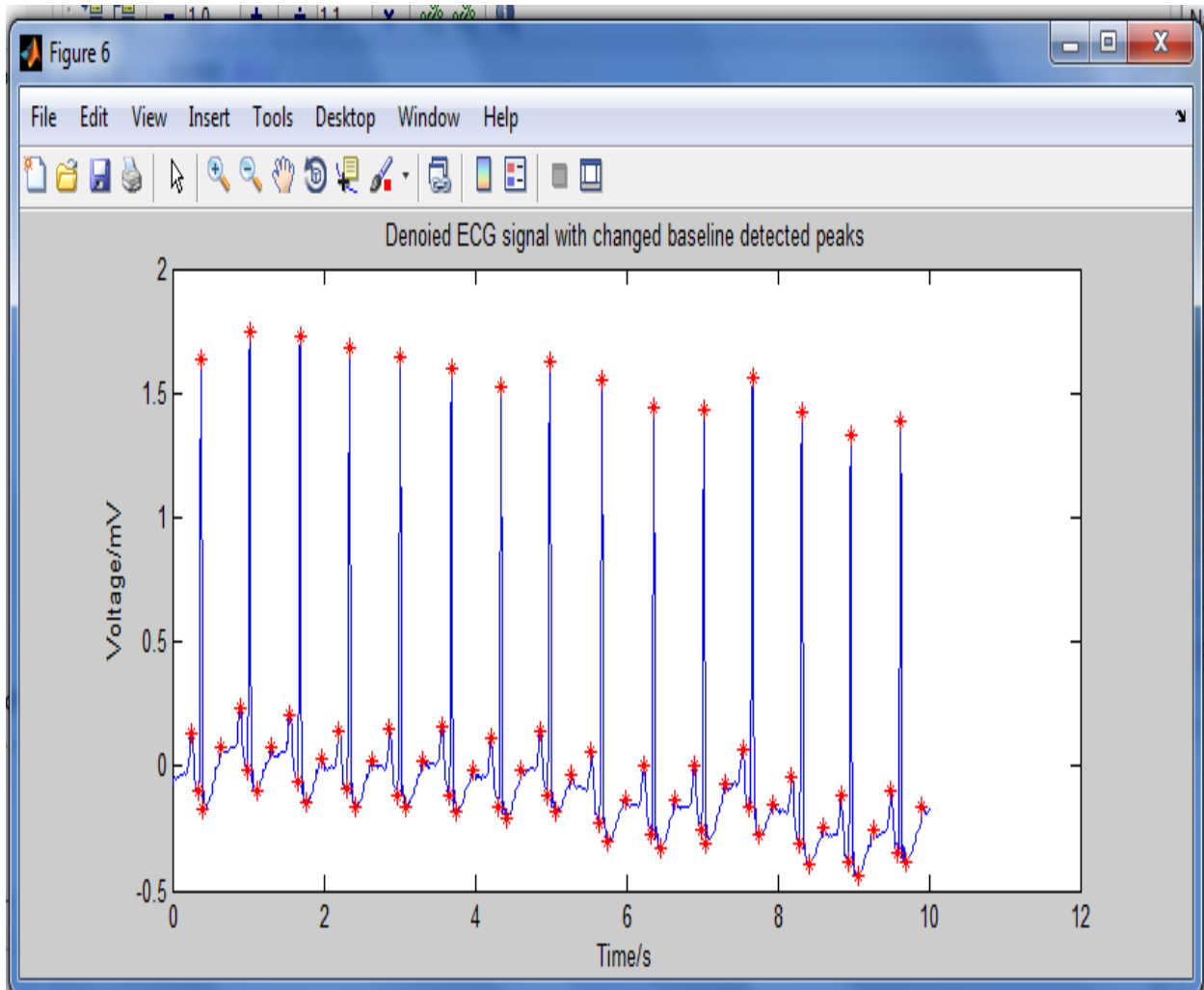
Figure 5.15. Showing That The ECG Signal Is Abnormal And The Percentage Of Noise Present In Original Ecg Signal

5.5. Results of The Different Datasets:-

S.No.	ECG Signal	Signal samples	Percentage of noise present in original ecg signal			Disease
			Coif	Db	Sym	
1	234m	3600	19.3162	22.8718	22.8718	Hypokalmia
2	100m	3600	32.9098	36.4707	36.4707	Hypokalmia
3	101m	3600	31.4957	34.0296	34.0296	Hypocalcemia, hypokalemia , bundle branch block
4	102m	3600	33.3774	35.9457	35.9457	Long QT Syndrome
5	103m	3600	17.5652	20.5853	20.5853	Hypocalcemia
6	104m	3600	22.7261	24.7262	24.7262	hypocalcemia hypokalmia sinus bradycardia
7	105m	3600	23.9291	26.8787	26.8787	bundle branch block Long QT Syndrome
8	106m	3600	21.6056	24.4875	24.4875	Right atrial enlagement
9	107m	3600	6.902	8.2466	8.2466	Right atrial enlagement hypokalmia Long QT Syndrome ventricular tachycardia
11	109m	3600	21.3855	24.9135	24.9135	atrio ventricular nodal reentrant tachycardia
12	111m	3600	34.0187	37.723	37.723	the ECG is normal
13	113m	3600	24.2408	26.1668	26.1668	Right atrial enlagement hypocalcemia hypokalmia bundle branch block

14	115m	3600	20.1547	22.6643	22.6643	hypocalcemia sinus bradycardia
15	116m	3600	8.6355	11.0618	11.0618	hypocalcemia
16	119m	3600	18.7101	21.6806	21.6806	Right atrial enlagement hypokalmia bundle branch block Long QT Syndrome
17	800m	1280	21.4084	23.9613	23.9613	Right atrial enlagement left Atrial enlargement Long QT Syndrome
18	802m	1280	16.1882	17.5988	17.5988	left Atrial enlargement Long QT Syndrome
19	810m	1280	14.9826	16.656	16.656	left Atrial enlargement
20	809m	1280	12.0441	13.8973	13.8973	Right atrial enlagement left Atrial enlargement Long QT Syndrome
21	808m	1280	9.9115	12.0663	12.0663	Right atrial enlagement left Atrial enlargement bundle branch block Long QT Syndrome
22	807m	1280	16.5757	18.0102	18.0102	Long QT Syndrome atrio ventricular nodal reentrant tachycardia
23	811m	1280	13.1046	16.1871	16.1871	Right atrial enlagement left Atrial enlargement Long QT Syndrome sinus bradycardia
24	812m	1280	18.8018			Right atrial enlagement Long QT Syndrome
25	822m	1280	33.086	35.3797	35.3797	left Atrial enlargement Long QT Syndrome sinus bradycardia
26	823m	1280	18.2291	20.2053	20.2053	Right atrial enlagement left Atrial enlargement bundle branch block Long QT Syndrome
27	824m	1280	10.4448	13.0355	13.0355	Right atrial enlagement left Atrial enlargement Long QT Syndrome sinus bradycardia

28	16265m	1280	10.669	12.4589	12.4589	left Atrial enlagement bundle branch block Long QT Syndrome
29	16272m	1280	18.4886	20.8637	20.8637	Right atrial enlagement bundle branch block Long QT Syndrome
30	16273m	1280	7.7635	9.4081	9.4081	Right atrial enlagement left Atrial enlargement bundle branch block
31	16420m	1280	9.1033	10.8017	10.8017	Right atrial enlagement left Atrial enlargement bundle branch block Long QT Syndrome
32	16483m	1280	11.1634	13.1695	13.1695	Right atrial enlagement left Atrial enlargement Long QT Syndrome
33	16539m	1280	10.0088	12.4204	12.4204	Long QT Syndrome atrio ventricular nodal reentrant tachycardia
34	16773m	1280	6.936	8.6301	8.6301	Right atrial enlagement left Atrial enlargement bundle branch block Long QT Syndrome
35	16786m	1280	8.722	10.5417	10.5417	left Atrial enlargement Long QT Syndrome
36	300m	3600	23.9371	27.9136	27.9136	Hypocalcemia
37	301m	3600	17.0404	20.0428	20.0428	hypocalcemia sinus bradycardia
38	302m	3600	15.3853	17.0745	17.0745	the ECG is normal
39	303m	3600	16.4037	20.5735	20.5735	hypercalcemia
40	304m	3600	20.6151	22.9037	22.9037	hypocalcemia sinus bradycardia
41	307m	3600	21.8407	24.528	24.528	sinus bradycardia
42	308m	3600	27.9889	33.223	33.223	atrio ventricular nodal reentrant tachycardia

43	309m	3600	11.1138	13.8306	13.8306	hypercalcemia
44	310m	3600	8.0643	10.2592	10.2592	Right atrial enlagement Long QT Syndrome ventricular tachycardia
45	311m	3600	18.3916	21.271	21.271	the ECG is normal
46	312m	3600	25.4147	28.3956	28.3956	he ECG is abnormal
47	313m	3600	17.6962	20.6288	20.6288	hypocalcemia

Chapter 6
Conclusion and future work

6.1. Conclusion:-

The proposed algorithm in this thsis can be used for accurate and fast feature extraction from any ECG signal and for further classification into normal and abnormal signal. The ECG signal has been properly analysed an errors have been effectively minimized. The baseline wander removal algorithm and subsequent segmentation into beats is very effective and lead to highly accurate feature extraction. The techniques used for feature extraction too are very efficient and show 99% accuracy. The original feature set was reduced to three features that were used for classification. The features and hence the classification is purely rhythm based. We have used a simple classifier but the features extracted are so distinct that they lead to highly accurate distinction between normal and abnormal ECG data.

This project was aimed to process ECG signals and analyse them so as to detect whether the signal is normal or abnormal. An exhaustive research and study was done before the initialization of the project. After having reviewed a slew of research papers related to biomedical engineering and ECG signal processing, Istarted the project and now, we finally have positive results as determined.

I have developed codes which first generate the ECG signal in matlab,then denoise the signal, remove the baseline wandering, detect the peaks and finally detect whether the signal is normal or abnormal and also detects the disease if abnormal.

I have been successful in denoising the original ECG signal completely using the wavelet transform method. The peaks are successfully detected and all the diseases that I have made algorithms for are also being accurately detected.

This path breaking research work can be potentially utilized for real time detection of disease if implemented on the hardware and can be very useful for doctors and organizations in the medical field. Advantages & Disadvantages Against Classical Techniques.

ECG baseline wandering removal advantage – no pre-processing phase.disadvantage – only stationary baseline (chirp, sinc signal – *future work*). ECG denoising advantage – improvement SNR disadvantage – only off-line processing (high computationally cost to perform on-line denoising) .ECG detection of QRS complex advantage – more universal (only one design parameter). disadvantage – worse performance due to the sensitivity to the onset and the offset steep (*future work).*

6.2. <u>Future Work:-</u>

ECG signal processing has wide application in the future generations. This automatic detection and interpretation of the ECG signal can be extensively utilized for the common people as they can test their heart-rate themselves. This can be possible by making use of new technologies in the field of Electronics and Communication Engineering, along with the advancements in Bio-medical engineering.

It can have wide application in the field of Biotelemetry. Biotelemetry is defined as transmitting biological or physiological data from a remote location to a location that has the capability to interpret the data and affect decision making. Biotelemetry is an important method for monitoring physiological variables by providing a wireless link between the subject and the data collection equipment. Biomedical data has been telemetered through every medium between two sites, including air, space, water and biologic tissue, by using a variety of modulated energy forms like electromagnetic waves, light, and ultrasound. One of the applications in biotelemetry is wireless Ambulatory ECG system. In such cases, the ECG signal is used to know the cardiac condition of an ambulatory patient. Wireless Ambulatory ECG recording is now routinely used to detect arrhythmias and cardiac abnormalities. As the ECG signal contains numerous artifacts, these artifacts have to be removed before monitoring, from the receiver point-of-view, so that a correct decision can be taken [34].

Another innovative application is an easy-to-use ECG Acquisition and Heart Rate Monitoring System Using a Wireless Steering Wheel [35]. Research has been carried out in this field and some propositions are made for the system. This system uses a dual ground

electrode configuration connected to a low-power analog front-end to reduce 50/60 Hz interference and it is able to show a stable ECG signal with good enough quality for monitoring purposes in less than 5 s. A novel heart rate detection algorithm based on the continuous wavelet transform has been implemented, which is specially designed to be robust against the most common sources of noise and interference present when acquiring the ECG in the hands, i.e., electromyographic (EMG) noise and baseline wandering. The algorithm shows acceptable performance even under non-ordinary high levels of EMG noise and yields a positive predictivity value of 100.00% and a sensitivity of 99.75% when tested in normal use with subjects of different age, gender, and physical condition [35].

Apart from these, we have a vision that ECG signal processing can be possible using very small hardware which can be incorporated into our mobile phones and we can check our heart-rate and rhythm through our phones itself. Applications can be developed by implementing the codes made for detection of the diseases and one can regularly check their ECG's by themselves, by just downloading the application. This would be cost effective and very helpful for aged people as they have more risks of heart diseases compared to the younger ones.

The interpretive statements that are designed are to aid the clinician—not be the sole factor for diagnosing or making transport decisions. They help clinicians make a more comprehensive diagnosis of a patient's cardiac condition.

All these future prospects of taking the ECG signal processing to the next level and making it more user-friendly will require a lot of research and determination and hence, there is a lot of scope for research in this field of bio-medical engineering and it can positively be achieved if meticulous work is carried out in this field.

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