A

SEMINAR REPORT

On

Ischemia Detection: By Identification of Isoelectric Line and ST Segment

Under Guidance of

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Declaration

*I hereby declare that the report entitled "**Ischemia Detection: By Identification of Isoelectric Line and ST Segment** " is an authentic record of my own work carried out as requirements for the award of degree of M.E. (Electronic Instrumentation & Control) at Thapar University, Patiala, under the guidance of Dr. Mandeep Singh (AP, EIED) during January to July 2010.*

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Acknowledgment

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Place: Thapar University, Patiala

Date: 24 JUNE, 2010

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Abstract

In this research work we present an algorithm for the automated detection of ST deviation that can be useful in diagnosing Coronary Heart Disease (CHD) using electrocardiogram (ECG) recordings. The technique is developed using Long Term ST database (LTST DB). Preprocessing is carried out prior to the extraction of ST segment which includes noise filtering using seven-point parabolic filter and then application of Wavelet Transform for QRS detection. The algorithm determines the R-peak detection in large number of samples, and then estimates the ST-segment's relative level with respect to iso-electric level using overlapping band selection method. It then compares the two levels, which is later used for ischemia detection. The performance of the proposed solution was evaluated on 14 records from LTST database. We found that there is reasonable amount of accuracy (98.5%) and it can therefore be concluded that the algorithm which have proposed can be used for most of the practical purposes.

Organization of Thesis

The first chapter introduces the Functioning of Heart, ischemia, its causes, types. A description of Cardiac Ischemia, Myocardial Infarction, ECG and its parameters and the technique used in ischemia detection algorithm i.e: Wavelet Transform

The second chapter tells about the work that has been already carried out in this field.

The third chapter formulates the problem.

The fourth chapter gives the detailed description of proposed solution with an algorithm and implementation of various tools of application software.

The fifth chapter shows the result obtained from the program in the tabular form and finally, thesis concluded in this chapter with future scopes.

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Abbreviations

CHD	Coronary Heart Disease
AV	Atrioventricular node
SA	Sinoatrial Node
TIA	Transient Ischemic Attack
MI	Myocardial Infarction
AMI	Acute Myocardial Infarction
RCA	Right Coronary Artery
LCA	Left Coronary Artery
ECG	Electrocardiogram
STEMI	ST Segment Elevation Myocardial Infarction
NSTEMI	Non-ST Segment Elevation Myocardial Infarction
STFT	Short Time Fourier Transform
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
PCA	Principal Component Analysis
NLPCA	Non Linear Principal Component Analysis
DFT	Discrete Fourier Transform
DCT	Discrete Cosine Transform
KLT	Karhunen Loeve Transform
ANN	Artificial Neural Network

LTST-DB	Long Term ST Database
db1	Daubechie wavelet of order 1

CHAPTER-1

Introduction

1.1 Functioning of Heart

The heart is a specialised muscle that contracts regularly and continuously, pumping blood to the body and the lungs. The pumping action is caused by a flow of electricity through the heart that repeats itself in a cycle. If this electrical activity is disrupted - for example by a disturbance in the heart's rhythm known as an arrhythmia - it can affect the heart's ability to pump properly. The heart has four chambers: the atria and the ventricles. The normal trigger for the heart to contract arises from the heart's natural pacemaker, the SA node, which is in the top chamber. The SA node sends out regular electrical impulses causing the atrium to contract and to pump blood into the bottom chamber (the ventricle).

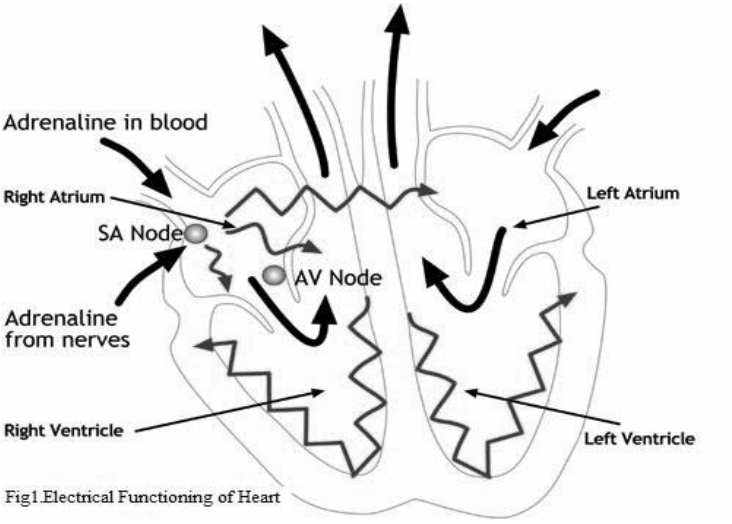


Fig1.1 Electrical Functioning of Heart

The electrical impulse then passes to the ventricles through a form of 'junction box' called the AV node (atrio-ventricular node). This electrical impulse spreads into the ventricles, causing the muscle to contract and to pump blood to the lungs and the body. Chemicals which circulate in the blood, and which are released by the nerves that regulate the heart, alter the speed of the pacemaker and the force of the pumping action of the ventricles. For example, adrenaline increases the heart rate and the volume of blood pumped by the

heart. Heart disease is the one of the leading causes of death all over the world with Myocardial Ischemia and Infarction called Coronary Heart Disease or CHD being the most common among these cardiac disorders. Myocardial Ischemia and Infarction results from the insufficient blood supply to the heart muscles (myocardium) due to blockages in the coronary artery, which is responsible for providing blood to the heart.

1.2 Ischemia

In medicine, **ischemia** (Isch – is restriction, hema or haema is blood) is a restriction in blood supply, generally due to factors in the blood vessels, with resultant damage or dysfunction of tissue. Ischemia is an absolute or relative shortage of the blood supply to an organ, i.e. a shortage of oxygen, glucose and other blood-borne fuels. A relative shortage means the mismatch of blood supply (oxygen/fuel delivery) and blood request for adequate metabolism of tissue. Ischemia results in tissue damage because of a lack of oxygen and nutrients. Ultimately, this can cause severe damage because of the potential for a build-up of metabolic wastes.

Ischemia is considered to be a major complication of the cardiac function, and a prime cause for the occurrence of cardiac infarction and dangerous cardiac arrhythmias.

1.2.1 Mechanism

Hypoxia is a general term denoting a shortage of oxygen, usually a result of lack of oxygen in the air being breathed but in comparison ischemia is an absolute or relative shortage of the blood supply to an organ, i.e. a shortage of oxygen, glucose and other blood-borne fuels. A relative shortage means the mismatch of blood supply (oxygen/fuel delivery) and blood request for adequate metabolism of tissue. Ischemia results in tissue damage because of a lack of oxygen and nutrients. Ultimately, this can cause severe damage because of the potential for a build-up of metabolic wastes.

Ischemia can also be described as an inadequate flow of blood to a part of the body, caused by constriction or blockage of the blood vessels supplying it.

1.2.2 Causes

1.2.2.1 Compression of Blood Vessels : Blood vessels can be compressed from the outside by growths. Tumors can press on major arteries blocking oxygen pathways, resulting in ischemia. Where other factors do not exist, ischemic episodes may indicate either the presence of cancer or large benign tumors.

1.2.2.2. Ventricular Tachycardia : Ventricular Tachycardia is a series of sudden irregular heartbeats that can cause the heart to function incorrectly, or in the most severe cases to stop completely. Resultant complications can include ischemia, since significant arrhythmias causing irregular heart function may also inhibit oxygen flow. In cardiac death as a result of ventricular tachycardia, the heart stops completely, depriving the entire body of oxygen. Though a person can be revived with the use of a defibrillator, length of oxygen deprivation may have caused damage to major organs.

1.2.2.3. Plaque Build-Up in Arteries (Atherosclerosis) : Atherosclerosis is the narrowing of arteries caused by the build-up of plaque. This is frequently seen in the elderly, and can usually be corrected. However, ischemia may first present when an artery becomes so completely blocked that blood cannot get to the brain or lungs. As well, narrow passageways make it easier for blood to clot and completely block the arteries.

1.2.2.4. Blood Clots : Blood clots can be caused by people having a high platelet count, by surgical procedures, or in those taking an excess of blood clotting agents. As well, some blood clots can form in the legs of those who are inactive. In very rare cases, blood clots can form in the legs during long airplane flights, causing almost immediate ischemia. Often blood clots are too small to block veins and arteries, but occasionally a large clot can block blood flow to a major organ, creating great damage.

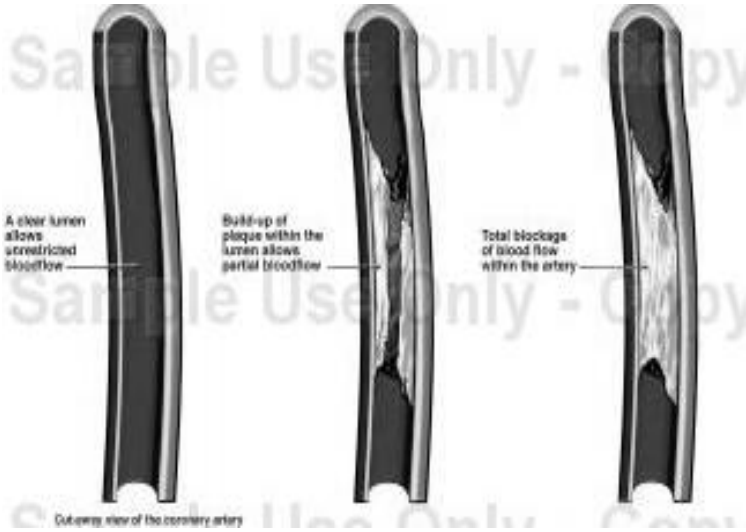


Fig1.2.Plaque build up in arteries

1.2.2.5. Extremely Low Blood Pressure as Caused by Heart Attack : One suffering a heart attack usually exhibits extremely low blood pressure, which represents inadequate oxygenation of tissues. Untreated and undiagnosed heart attacks can slow blood flow enough that clots are formed creating ischemic conditions. Those who have had repeated heart attacks may be at greater risk for ischemia.

1.2.2.6. Congenital Heart Defects: Those with congenital heart defects are also at increased risk for ischemia due to clotting, both before and after reparative surgery. Some with congenital heart defects are at immediate risk for ischemia at birth, due to lack of appropriate artery formation, artery connection or missing arteries.

1.2.2.7. Sickle Cell Anemia: It can cause ischemia because irregularly or sickle shaped blood cells can clot more easily, blocking oxygen rich blood to either the heart, lungs or brain. Rarely, a clot can block passage of oxygen to other organs like the liver, creating significant damage. Most with Sickle Cell Anemia take anti-clotting medications to prevent ischemia.

1.2.3 Ischemia Types

1.2.3.1.Cutaneous Ischemia

Reduction in blood flow to the skin layers may result in mottling or uneven, patchy discoloration of the skin. It may cause due to any blockage that may cause due to plaque formation,due to blood clots in the arteries or blood vessels or due to compression of blood vessels.

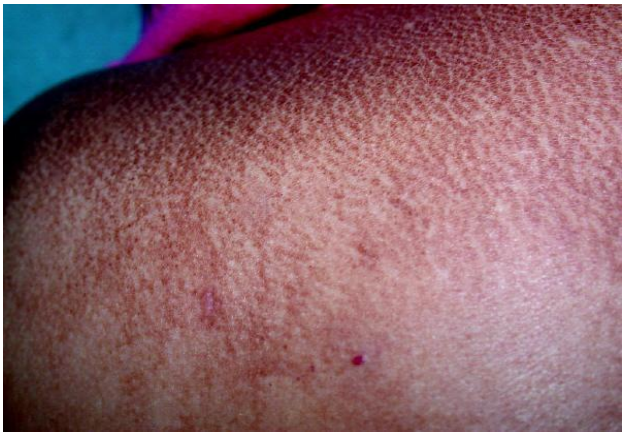


Fig1.3.Discoloration of skin(cutaneous ischemia)

1.2.3.2.Cerebral Ischemia

It occurs in the arteries of the brain, where blockages can lead to a stroke**.** Most blockages in the cerebral arteries are due to a blood clot, often in an artery narrowed by plaque. Sometimes, a blood clot in the heart or aorta travels to a cerebral artery. A transient ischemic attack(TIA) is a "mini-stroke" caused by a temporary deficiency of blood supply to the brain. It occurs suddenly, lasts a few minutes to a few hours, and is a strong warning sign of an impending stroke. Ischemia can also effect intestines, legs, feet and kidneys. Pain, malfunctions, and damage in those areas may result.

A stroke is a partially fatal event in which the part of the brain doesnot get enough oxygen. It occurs either due to lack of oxygen rich blood to the brain or due to bleeding around the brain.

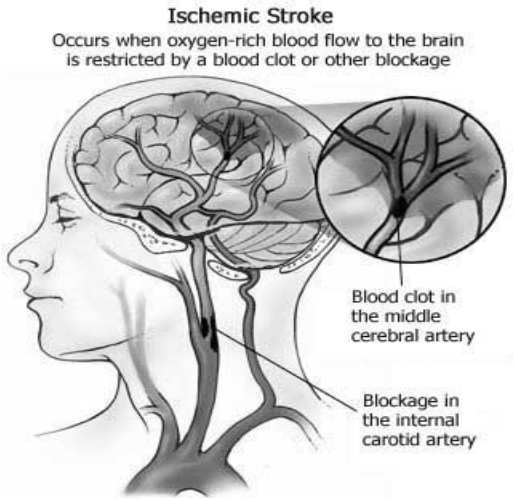


Fig1.4.Blood clot in the middle cerebral artery leads to cerebral ischemia

1.2.3.3. Bowel Ischemia

A person with ischemic bowel disease has narrowing of the arteries that supply blood and oxygen to the intestines. As the narrowing worsens, the arteries become unable to supply enough oxygen to meet demand. This can cause abdominal pain and damage to the intestine. Ischemic bowel disease is caused by hardening of the arteries, called atherosclerosis. It is rare in those who are less than 50 years old.

Symptoms of bowel ischemia are :

(i) Abdomen Pain,
(ii) Blood in the stool,
(iii) Black stool,
(iv) Diarrhea,
(v) Constipation.

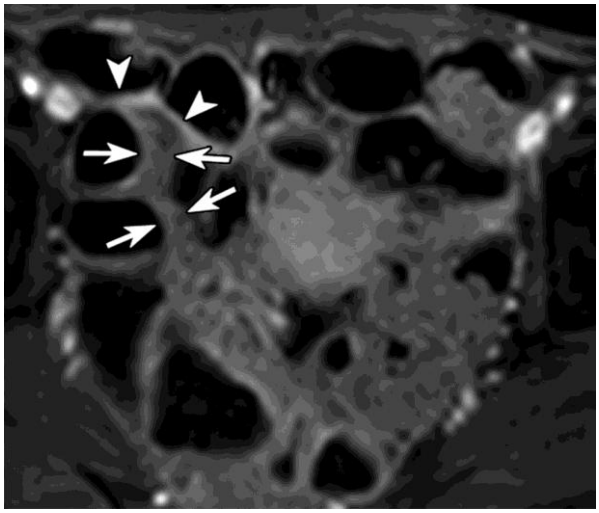


Fig1.5.Bowel Ischemia(Intestine)

1.2.3.4 Cardiac Ischemia

Cardiac ischemia is a situation in which the flow of oxygen-rich blood to the heart muscle is impeded, resulting in inadequate oxygenation of the heart. The most common cause of cardiac ischemia is plaque buildup in the arteries due to the long-term effects of coronary artery disease. This plaque buildup narrows the arteries to the point where the amount of blood flowing through the arteries is not enough to supply oxygen-rich blood to the heart, especially during times of physical exertion or emotional stress.

CARDIAC ISCHEMIA

1.3 Myocardial/Cardiac Ischemia

Myocardial ischemia is the most common cardiac disease and it is caused by a lack of sufficient blood flow to the contractile cells and may lead to myocardial infarction. The most common cause of cardiac ischemia is plaque buildup in the arteries due to the long-term effects of coronary artery disease. The development of plaque within the coronary artery that blocks more than 70% of the lumen of the vessel can cause symptoms of myocardial ischemia, such as decreased exercise tolerance and exertional angina, to appear. At times, this may be the first instance where the subject begins to experience effects of the suboptimal operation of the heart due to decreased blood supply. The main characteristic of ischemia in the cellular level is the depolarization of the cellular resting membrane potential. As large areas of the heart muscle become ischemic, its relaxation and contraction patterns are affected, which cause variations in the ST level and T-wave in electrocardiogram (ECG) due to the development of an injury current between the ischemic and non-ischemic regions of the heart. The ST level change episodes lasting several seconds or sometimes some minutes, is an important indication in the diagnosis of myocardial ischemia. Repeated ischemia may lead to tissue injury and changes in electrophysiological properties that may in turn predispose the heart to arrhythmias.

The ischemic region is classified as subendocardial or transmural. Subendocardial ischemia begins at the endocardial surface, the region furthest from the blood supply, and extends partially through the heart wall. If the ischemic region extends from the endocardium through to the epicardium then it is classified as transmural ischemia.

The lack of oxygen is often temporary, and symptoms can include a type of chest pain, pressure or discomfort called angina. These episodes may last anywhere from 2 to 20 minutes. However, many episodes of ischemia do not have any associated symptoms (silent ischemia).

Lengthy episodes of cardiac ischemia can be a sign of a heart attack. A heart attack occurs when a blood clot blocks the flow of blood to the heart muscle. It can occur in an artery already narrowed by plaque (atherosclerosis), or a heart attack can occur after a blood clot breaks off from its original site and travels through the arteries. The blockage causes a sudden and possibly complete interruption of oxygen-rich blood flow, and the resulting heart attack could cause permanent damage and scarring to the portion of the heart muscle supplied by the blocked artery. Prevention and treatment are related to modifying the underlying factors that promote the development of atherosclerosis and blood clot formation.

Ischemia can be silent or symptomatic.

1. **Symptomatic ischemia** is characterized by chest pain called **angina pectoris.**
2. **Silent ischemia** usually is caused by emotional or mental stress or by exertion, but there are no symptoms.

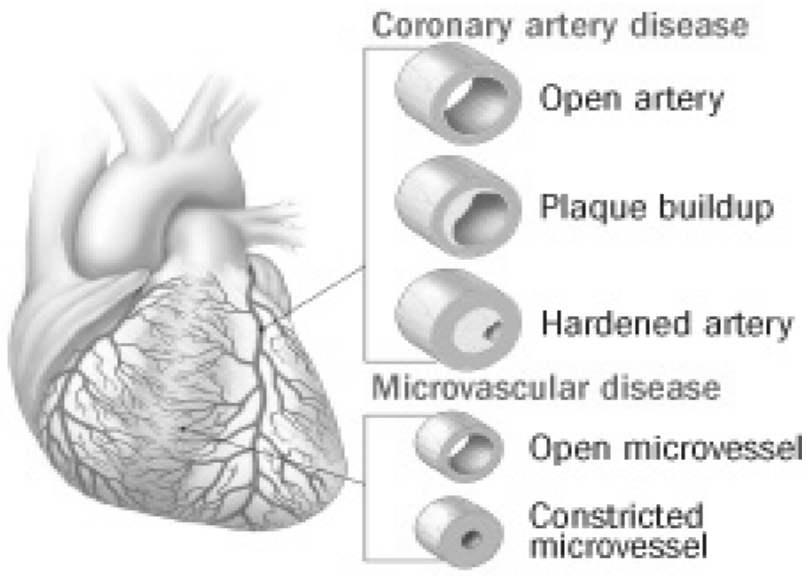


Fig1.6.:Myocardial ischemia

Minor episodes of cardiac ischemia tend to cause little long-term damage to the heart, but there may be serious side effects in some patients:

1) They can cause abnormal heart rhythms (arrhythmias), which can lead to either syncope (fainting) or cardiac arrest (the abrupt inability of the heart to pump blood) and sudden cardiac death.
2) Severe or lengthy episodes can trigger a heart attack.
3) The collective effects of minor episodes of cardiac ischemia can potentially lead to a weakening of the heart muscle (cardiomyopathy).

1.4 Angina Pectoris

Angina pectoris, commonly known as **angina**, is severe chest pain due to ischemia (a lack of blood and hence oxygen supply) of the heart muscle, generally due to obstruction or spasm of the coronary arteries (the heart's blood vessels). Coronary artery disease, the main cause of angina, is due to atherosclerosis of the cardiac arteries.

Myocardial ischemia comes about when the myocardia (the heart muscles) receive insufficient blood and oxygen to function normally either because of increased oxygen demand by the myocardia or by decreased supply to the myocardia. This inadequate perfusion of blood and the resulting reduced delivery of oxygen and nutrients is directly correlated to blocked or narrowed blood vessels.

1.4.1 Types of Angina

1.Stable angina

2.Unstable angina

1.4.1.1 Stable Angina: Stable angina occurs during exertion, can be quickly relieved by resting or taking nitroglycerin, and lasts from three to twenty minutes.

1.4.1.2 Unstable angina: Unstable angina increases the risk of a heart attack, occurs more frequently, lasts longer, is more severe, and may cause discomfort during rest or light exertion.

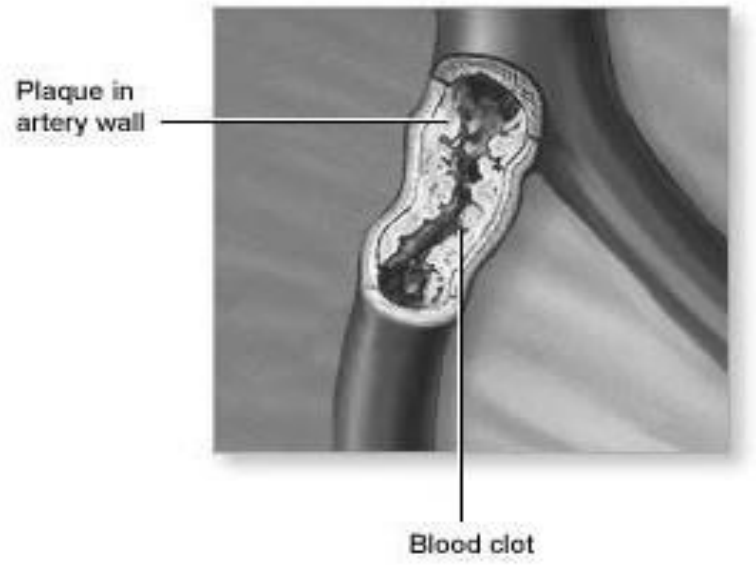


Fig1.7Plaque formation and blood clots in the arteries'walls

1.5 Myocardial Infarction

Myocardial infarction (**MI**) or **acute myocardial infarction** (**AMI**), commonly known as a **heart attack**, is the interruption of blood supply to part of the heart, causing some heart cells to die. This is most commonly due to occlusion (blockage) of a coronary artery following the rupture of a vulnerable atherosclerotic plaque, which is an unstable collection of lipids (fatty acids) and white blood cells (especially macrophages) in the wall of an artery. The resulting ischemia (restriction in blood supply) and oxygen shortage, if left untreated for a sufficient period of time, can cause damage or death (infarction) of heart muscle tissue (myocardium).

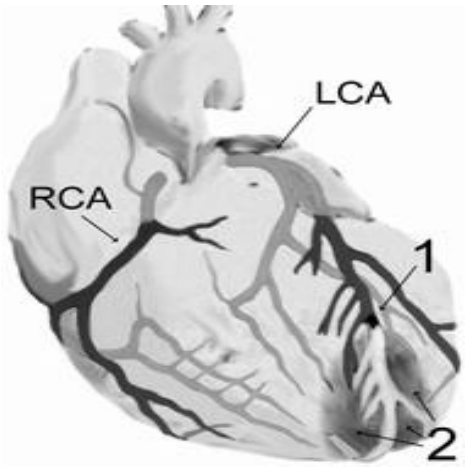


Fig1.8 Diagram of a myocardial infarction (2) of the tip of the anterior wall of the heart (an apical infarct) after occlusion (1) of a branch of the left coronary artery

1.5.1 Causes Of Heart Attack

1. Cardiovascular disease such as Angina.
2 High levels of low density lipoprotein or good cholesterol.
3 Low level of high density lipoprotein or bad cholesterol.
4 Smoking or tobacco.
5 Diabetes.
6 High blood pressure.
7 Obesity.

1.5.2 Signs And Symptoms

1. Chest pain
2. A tight, squeezing, heavy, burning, or choking pain that is usually beneath the breastbone—the pain may spread to the throat, jaw, or one arm.
3. Chest discomfort rather than actual pain: the discomfort is usually described as a pressure, heaviness, tightness, squeezing, burning, or choking sensation..
4. A feeling similar to gas or indigestion .
5. Attacks brought on by exertion and relieved by rest.
6. Shortness of breath and sweating.

1.6 Electrocardiogram(ECG)

The electrocardiogram (ECG or EKG) is a diagnostic tool that measures and records the electrical activity of the heart in exquisite detail. Interpretation of these details allows diagnosis of a wide range of heart conditions. These conditions can vary from minor to life threatening. The ECG is a graphic record of the direction and magnitude of the electrical activity that is generated by depolarization and repolarization of the atria and ventricles. One cardiac cycle in an ECG signal consists of the P-QRS-T waves. Most of the clinically useful information in the ECG is found in the intervals and amplitudes defined by its features (characteristic wave peaks and time durations). The development of accurate and quick methods for automatic ECG feature extraction is of major importance, especially for the analysis of long recordings.
The ECG has evolved over the years.

1. The standard 12-lead ECG is used.
2. It is called a 12-lead ECG because it examines the electrical activity of the heart from 12 points of view.
3. This is necessary because no single point (or even 2 or 3 points of view) provides a complete picture of what is going on.

1.6.1 Heart Function And The ECG

The heart normally beats between 60 and 100 times per minute, with many normal variations. For example, athletes at rest have slower heart rates than most people. This rate is set by a small collection of specialized heart cells called the sinoatrial (SA) or sinus node.

Located in the right atrium, the sinus node is the heart's "natural pacemaker."

1. It has "automaticity," meaning it discharges all by itself without control from the brain.

2. Two events occur with each discharge: (1) both atria contract, and (2) an electrical impulse travels through the atria to reach another area of the heart called the atrioventricular (AV) node, which lies in the wall between the 2 ventricles.

3. The AV node serves as a relay point to further propagate the electrical impulse.

4. From the AV node, an electrical wave travels to both ventricles, causing them to contract and pump blood.

5. The normal delay between the contraction of the atria and of the ventricles is 0.12 to 0.20 seconds. This delay is perfectly timed to account for the physical passage of the blood from the atrium to the ventricle. Intervals shorter or longer than this range indicate possible problems.

   The ECG records the electrical activity that results when the heart muscle cells in the atria and ventricles contract.

6. Atrial contractions (both right and left) show up as the P wave.

7. Ventricular contractions (both right and left) show as a series of 3 waves, Q-R-S, known as the QRS complex.

8. The third and last common wave in an ECG is the T wave. This reflects the electrical activity produced when the ventricles are recharging for the next contraction (repolarizing).

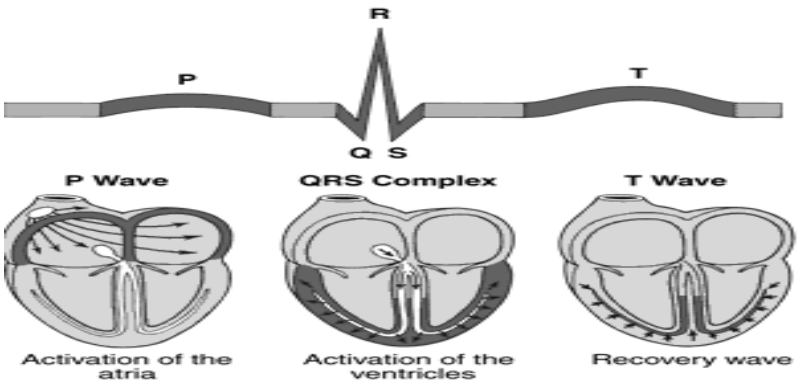


Fig1.9.:Heart Functioning

1.6.2 Waves And Intervals

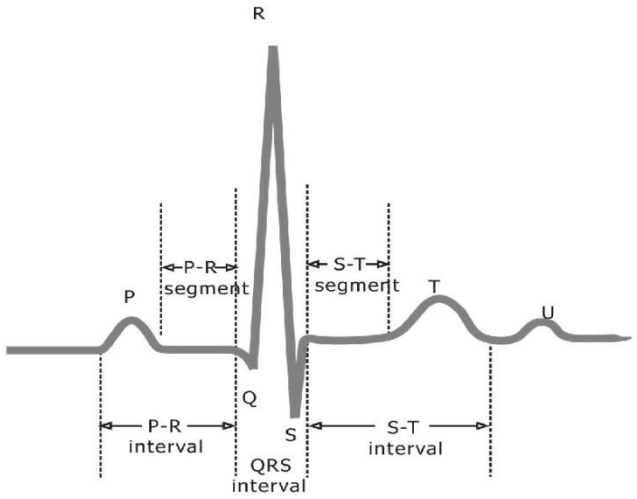


Fig1.10.One-cycle ECG tracing is shown.

Feature	Description	Duration
P-Wave	During normal atrial depolarization, the main electrical vector is directed from SA node towards the AV node, and spreads from the right atrium to the left atrium. This turns into the P wave on the ECG.	80ms
QRS Complex	The QRS complex corresponds to the depolarization of the right and left ventricles.	70-110ms
ST segment	The ST segment connects the QRS complex and the T wave.	80-120ms
T-Wave	The T wave represents the repolarization (or recovery) of the ventricles. The interval from the beginning of the QRS complex to the apex of the T wave is referred to as the absolute refractory period. The last half of the T wave is referred to as the relative refractory period (or vulnerable period).	160ms
PR interval	The PR interval is measured from the beginning of the P wave to the beginning of the QRS complex.	120-200ms

ST interval	The ST interval is measured from the J point to the end of the T wave.	320ms
QT interval	The QT interval is measured from the beginning of the QRS complex to the end of the T wave.	300-430ms

Table1.1 ECG parameters description

1.7 ST Segment

The ST interval is measured from the J point to the end of the T wave. The **S** point is identified as the first inflection after the Rwave. In normal ECG, the **S** point can be recognised as a relative minimum after the R-wave. Generally, it can be recognised by a change in the slope of the ECG signal. The T-wave is the inflection after the **S** point and within 0.75 of the RR interval. Ischaemia is caused by insufficient blood supply to the heart muscle. The most important ECG change caused by myocardia1 ischemia is the ST elevation on the epicardium **.** It relates to a delay in conduction velocity due to accumulation of **[K+]** in the ischemic zone relative to the normal zone. This causes a depolarization of the resting membrane potential and leads to ST elevation and TQ depression. The ST-level is widely being used as an electrocardiographic indicator of ischemic states of the myocardium during physical stress and silent ischemia episodes.
Unfortunately, not all ischemic states are reflected by the ST-level on the body surface, and not all ECG leads respond to time-varying coronary perfusion by means of ST-level changes. The extent of subendocardial underperfusion and related transmural potential gradients were shown to strongly influence the ST measure during ischemia. Elevation and depression of the ST segment together with the T-wave changes indicate the zone of ischaemia around the applied lead. Therefore, the ST slope is the most important feature of the ECG for investigating myocardial ischaemia. The ST level is the maximum deviation from the isoelectric level.

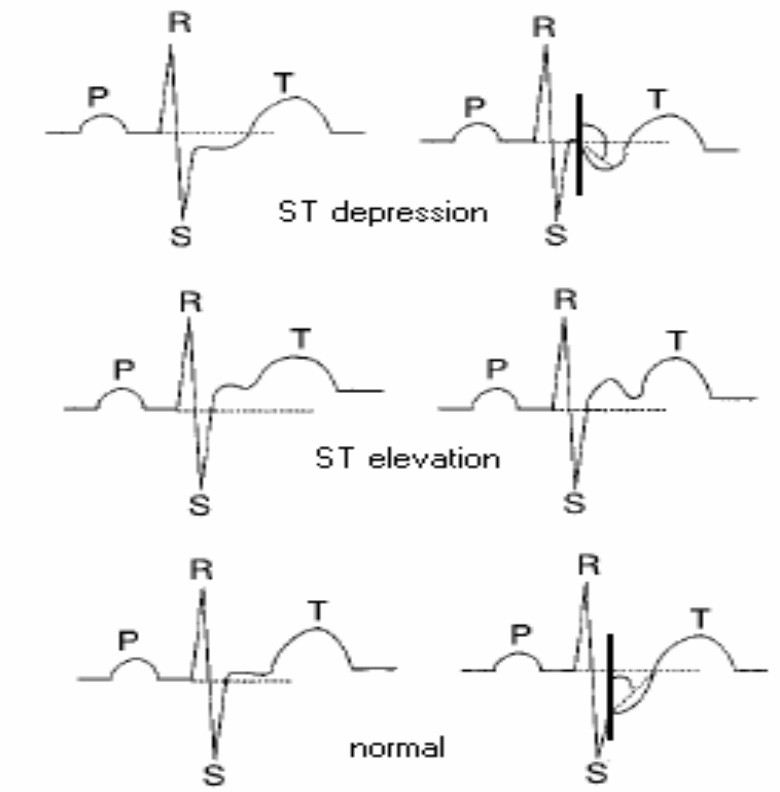


Fig1.11 Negative ST Deviation (top row), positive ST deviation (middle row) and normal (bottom row)

1.7.1 STEMI and NSTEMI

STEMI is an acronym meaning "ST segment elevation myocardial infarction," which is a type of heart attack. This is determined by an electrocardiogram (ECG) test.

Myocardial infarctions(heart attacks) occur when a coronary artery suddenly becomes at least partially blocked by a blood clot, causing at least some of the heart muscle being supplied by that artery to become infarcted (that is, to die). Heart attacks are divided into two types, according to their severity. A STEMI is the more severe type.

In a STEMI, the coronary artery is completely blocked off by the blood clot, and as a result virtually all the heart muscle being supplied by the affected artery starts to die.

This more severe type of heart attack is usually recognized by characteristic changes it produces on the ECG. One of those ECG changes is a characteristic elevation in what is

called the "ST segment." The elevated ST segment indicates that a relatively large amount of heart muscle damage is occurring (because the coronary artery is totally occluded), and is what gives this type of heart attack its name.

NSTEMI

NSTEMI is an acronym meaning "non-ST segment elevation myocardial infarction," which is a type of heart attack. This is determined by a electrocardiogram (ECG) test.

Myocardial infarctions (heart attacks) occur when a coronary artery suddenly becomes occluded by a blood clot, causing at least some of the heart muscle being supplied by that artery to become infarcted (that is, to die). Myocardial infarctions are divided into two types, according to their severity. A NSTEMI is the less severe type.

In a NSTEMI, the blood clot only partly occludes the artery, and as a result only a portion of the heart muscle being supplied by the affected artery dies.

In contrast to the more severe form of heart attack (the STEMI), the NSTEMI does not produce characteristic elevation in the "ST segment" portion of the ECG. (ST segment elevation indicates that a relatively large amount of heart muscle damage is occurring, because the coronary artery is totally blocked). This means that in a NSTEMI, the artery is only partially blocked.

1.7.2 ST Segment Depression

ST segment depression can be caused by ischemia, digitalis, rapid heart rate, and temperature or electrolyte abnormality. It can also be a “reflected” or reciprocal ST elevation (showing an inverted view of what’s happening at another place in the heart). The shape of the ST segment, and whether the abnormality is localized to leads looking at one area of the heart, often allows the cause of ST depression to be diagnosed. ST segment depression is considered significant if the ST segment is at least one box below baseline, as measured two boxes after the end of the QRS. As with infarction, the location

of the ischemia is reflected in the leads in which the ST depression occurs. When ST deviation is more than 0.08 mV below the isoelectric line and has an angle larger than 65degree measured from vertical line, it is considered as negative ST deviation or ST depression. The second rule classifies beat as ischemic if ST deviation is more than 0.08 mv above the isoelectric line (ST elevation).

1.8 Isoelectric Line

Isoelectric line is the flat parts of the ECG, for example between the T and P waves or between the P wave and the QRS complex.

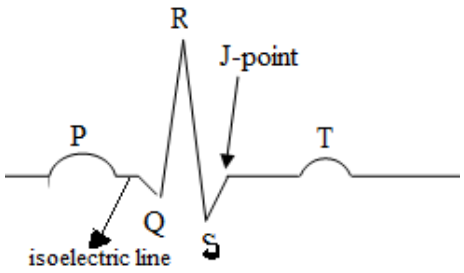


Fig1.12 Isoelectric line between P wave and QRS complex

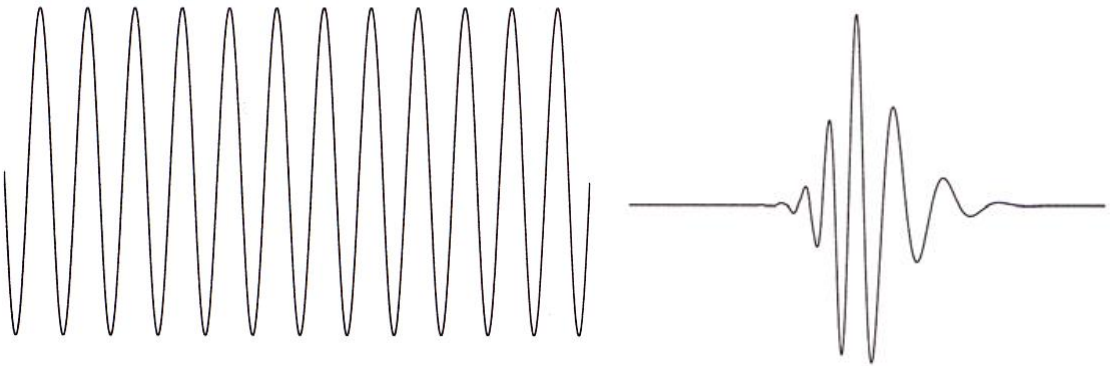
ST segment's relative level with respect to isoelectric level can be determined which is used for ischemia detection. If this segment is significantly below the isoelectric line it is called ST segment depression and it suggests that part of the subject's myocardium is not getting enough oxygen (myocardial ischema). This segment is also frequently elevated (ST segment elevation) above the isoelectric line in the early stages of a myocardial infarction.

1.9 Wavelet Transform

The transform of a signal is just another form of representing the signal. It does not change the information content present in the signal. The Wavelet Transform provides a time-frequency representation of the signal. It was developed to overcome the short coming of the Short Time Fourier Transform (STFT), which can also be used to analyze

non-stationary signals. While STFT gives a constant resolution at all frequencies, the Wavelet Transform uses multi-resolution technique by which different frequencies are analyzed with different resolutions.

A wave is an oscillating function of time or space and is periodic. In contrast, wavelets are localized waves. They have their energy concentrated in time or space and are suited to analysis of transient signals. While Fourier Transform and STFT use waves to analyze signals, the Wavelet Transform uses wavelets of finite energy.



(a) (b)

Figure 1.13 Demonstration of (a) a Wave and (b) a Wavelet

The wavelet analysis is done similar to the STFT analysis. The signal to be analyzed is multiplied with a wavelet function just as it is multiplied with a window function in STFT, and then the transform is computed for each segment generated. However, unlike STFT, in Wavelet Transform, the width of the wavelet function changes with each spectral component. The Wavelet Transform, at high frequencies, gives good time resolution and poor frequency resolution, while at low frequencies, the Wavelet Transform gives good frequency resolution and poor time resolution.

1.9.1 The Continuous Wavelet Transform and the Wavelet Series

The Continuous Wavelet Transform (CWT) is provided by equation 2.1, where x(t) is the signal to be analyzed. $\psi(t)$ is the mother wavelet or the basis function. All the wavelet functions used in the transformation are derived from the mother wavelet through translation (shifting) and scaling (dilation or compression).

$$X_{WT}(\tau,s) = 1/\sqrt{|s|} \int x(t) \cdot \Psi * \left(\frac{t-\tau}{s}\right)$$

The mother wavelet used to generate all the basis functions is designed based on some desired characteristics associated with that function. The translation parameter τ relates to the location of the wavelet function as it is shifted through the signal. Thus, it corresponds to the time information in the Wavelet Transform. The scale parameter *s* is defined as |1/frequency| and corresponds to frequency information. Scaling either dilates (expands) or compresses a signal. Large scales (low frequencies) dilate the signal and provide detailed information hidden in the signal, while small scales (high frequencies) compress the signal and provide global information about the signal.

1.9.2 Discrete Wavelet Transform

The Wavelet Series is just a sampled version of CWT and its computation may consume significant amount of time and resources, depending on the resolution required. The Discrete Wavelet Transform (DWT), which is based on sub-band coding is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required.

In CWT, the signals are analyzed using a set of basis functions which relate to each other by simple scaling and translation. In the case of DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cutoff frequencies at different scales.

CHAPTER-2

Literature Survey

2.1 Recognition of the Shape of the ST Segment in ECG Waveforms

In October 1986, E. Skordalakis presented a method which recognizes the shape of the ST segment. This method when applied to an ST segment gives as results of the onset and the end of the ST segment and the equation of a straight line or of a parabola that best approximates this ST segment. The method is based on the idea that since the ST segment is supposed to be either a line segment or a parabolic segment, its recognition can be made by approximating it first by a straight line and then by a parabola, and choosing among these two approximations the one with the smaller error norm. Such a method for the recognition of the ST segment cannot be implemented because in actual practice it is very difficult to calculate the endpoint of the ST segment. A way to overcome this difficulty is to take a segment larger than the ST segment but with the following constraints: 1) it incorporates the ST segment, 2) its onset as well as its end can be reliably calculated, and 3) it can be divided into subsegments in such a way that one of them is the ST segment. The method presented in this paper has not been gone through a strict evaluation procedure because of lack of a test set of data. Despite it, it can be said that the results taken so far are satisfactory and so the method deserves consideration.

2.2 Detection And Extraction Of The Ecg Signal Parameters

In 1998, H. Gholam - Hosseini et. al presented a set of efficient techniques to extract important features from the ECG data applicable in automatic cardiac arrhythmia classification. The selected parameters are divided into two main categories namely morphological and statistical features. Extraction of morphological features were achieved using signal processing techniques and detection of statistical features were

performed by employing mathematical methods. The morphological features are found most effective method for further ECG signal analysis and the mathematical approach is preferred for a precise and robust feature extraction. A computer based ECG signal classifier can be developed by employing the extracted features for detection of a vast range of cardiac arrhythmias.

2.3 ECG Analysis Using Nonlinear PCA Neural Networks for Ischemia Detection

In November,1998, T. Stamkopoulos, et. al is investigated that the detection of ischemic cardiac beats from a patient's electrocardiogram (ECG) signal is based on the characteristics of a specific part of the beat called the ST segment. An algorithm is developed for this feature extraction based on nonlinear principal component analysis (NLPCA). NLPCA is a relatively recently proposed method for nonlinear feature extraction that is usually implemented by a multilayer neural network. The algorithm was tested in application to the detection of ischemic beats in ECG Holter recordings, which is one of the most important biomedical signal processing problems. The method apparently exhibits superior performance compared with other methods using PCA/NN for ischemic beat/episode detection.

2.4 Advanced Detection Of ST Segment Episodes In 24-Hour Ambulatory ECG Data By Automated Tracking Of Transient ST Segment Reference Level

In year 2002, A Smrdel, F.Jager developed an algorithm for automated detection of transient ST segment episodes in 24-hour ambulatory data. To detect ST change episodes, the algorithm automatically tracks the time-varying ST segment reference level due to clinically not important non-ischemic causes and subtracts it from the ST segment level. Tracking the ST segment reference level is crucial ability for the reliable ST segment episode detection, resulting in high sensitivity and positive perdictivity. Further improvements of the algorithm are planned by incorporating information of raw signal waveform.

2.5 Long-term ST database: a reference for the development and evaluation of automated ischaemia detectors and for the study of the dynamics of myocardial ischaemia:

In year 2003, F.Jager et. al goal was to develop a challenging and realistic research resource for development and evaluation of automated systems to detect transient ST segment changes in electrocardiograms and for supporting basic research into the mechanisms and dynamics of transient myocardial ischaemia. Twenty-four hour ambulatory ECG records were selected from routine clinical practice settings in the USA and Europe, between 1994 and 2000, on the basis of occurrence of ischaemic and nonischaemic ST segment changes. Human expert annotators used newly developed annotation protocols and a specially developed interactive graphic editor tool (SEMIA) that supported paperless editing of annotations and facilitated international co-operation via the Internet. The database contains 86 two- and three-channel 24 h annotated ambulatory records from 80 patients and is stored on DVD-ROMs. The database annotation files contain ST segment annotations of transient ischaemic (1155) and heart-rate related ST episodes and annotations of non-ischaemic ST segment events related to postural changes and conduction abnormalities. The database is intended to complement the European Society of Cardiology ST-T database and the MIT-BIH and AHA arrhythmia databases.

2.6 Simulation of ST Segment Changes During Subendocardial Ischemia Using a Realistic 3-D Cardiac Geometry

In May 2005, Mary C. MacLachlan , et. al investigated that a realistic three-dimensional model of the ventricles, including fiber rotation and anisotropy, is embedded in a nonhomogeneous torso model. A simplification of the bidomain model is used to calculate only the ST segment shift. The simulation results suggest that subendocardial ischemia can be located by ST segment shift on the epicardial and torso surfaces. Simulation results have shown both ST elevation and depression associated with the subendocardial ischemic region, elevation above the transmural boundary and depression

above the lateral boundaries. In this case, it appears that the precordial leads are facing the transmural boundary. Simulations presented here can be concluded that subendocardial ischemia is indeed locatable by ST segment shift above the ischemic region on both the epicardial and torso surfaces. The results show that both ST depression (lateral boundaries) and ST elevation (transmural boundary) can be associated with subendocardial ischemia.

2.7 A QRS detection method using analog wavelet transform in ECG analysis

In June 2005, M.J. Vaessen investigated that low power implementable devices like the pacemaker need good sensing circuits to correctly analyze the cardiac signal and take appropriate actions. Existing methods are reaching their limits on sensing abilities. An approximation of the wavelet transform (WT), that can be implemented in an analog dynamic translinear circuit, can be used to further the advances of cardiac signal sensing and lead to better pacemakers. A method is presented for automatic QRS complex detection in an ECG signal for use with an analog implementation of the wavelet transform. He concluded that by using the modulus maxima in the WT and the time differences between them, QRS complex detection rates are up to 98% on the MIT/BIH database.

2.8 ECG Feature Extraction Based on Multiresolution Wavelet Transform

In September 2005,S. Z. Mahmoodabad et al. have developed and evaluated an electrocardiogram (ECG) feature extraction system based on the multi-resolution wavelet transform. ECG signals from Modified Lead II (MLII) are chosen for processing. In the first step, the ECG signal was de-noised by removing the corresponding wavelet coefficients at higher scales. Then, QRS complexes are detected and each complex is used to locate the peaks of the individual waves, including onsets and offsets of the P and T waves which are present in one cardiac cycle. The proposed wavelet based feature extraction system achieved good detection performance on the MIT – BIH database. The QRS detector attained sensitivity of 99.18% 2.75 and a positive predictivity of 98.00% 4.45 on the first lead of the validation databases among 46 records.

2.9 Challenge 2006: QT Interval Measurement

In year 2006, R Schneider, A Bauer, et. al implemented an algorithm which performs beat detection, measures wave boundaries on a beat-to-beat basis and selects a representative beat whose QT interval is used. To get the positions of the wave boundaries, the algorithm searches for peaks in the 1st derivative of bandpass filtered ECG signals using thresholds which are adapted to the amplitudes in the segments of interest. When the peaks associated with the QRS complex and the T wave are found, the beginning of the QRS complex and the end of the T wave are assessed. The score of our approach is 70.94ms. the main reason for the poor performance of our approach is that we looked only in one lead and did not use the information of the other leads. Another deficit of our approach is the lack of plausibility checks. One simple plausibility check could be that only QT intervals between 250ms and 500ms are allowed all beats with a QT interval outside this range are excluded.

2.10 Detection of ST Segment Deviation Episodes in the ECG using KLT with an Ensemble Neural Classifier

In year 2007, Fayyaz A. Afsarl et. al describe a technique for the automatic detection of ST Segment deviations for the diagnosis of Coronary Heart Disease (CHD) using ambulatory ECG recordings through the application of lead-dependent Karhunen-Loeve Transform (KLT) bases for dimensionality reduction of ST Segment Data. Preprocessing is carried out prior to the extraction of the ST Segment which involves noise and artifact filtering using a digital band-pass filter, baseline removal and application of a Discrete Wavelet Transform (DWT) based technique for detection and delineation of the QRS Complex in the ECG. ST deviation episodes are detected by a classifier ensemble comprising of Back Propagation Neural Networks. A comparison of the proposed method with other techniques in the literature has done which shows that the proposed method outperforms all existing techniques for ST deviation. The results obtained through the use of this method, (Sensitivity/Positive Predictive Value) of (90.75%/89.2%) compare well with those given in existing research and exhibit the potential of this method to be adopted in the design of a practical ischemia detection system. These results can be

improved further but caution must be taken to evaluate the accuracies of the database annotations themselves as it can affect the generalization performance of the system on other databases.

2.11 Automatic Distinguishing Between Ischemic and Heart-Rate Related Transient ST Segment Episodes in Ambulatory ECG Records

In year 2008, J Faganeli, et.al investigated that ischemia is manifested by transient ST segment episodes which may or may not be accompanied by increase in heart rate. There can also be transient non-ischemic ST segment morphology-change episodes which are not caused by an obstruction of the blood flow to the heart, but are caused by simultaneous change in heart rate. These transient non-ischemic heart-rate related ST segment episodes complicate automatic detection of true ischemia. The goal of this work was to automatically distinguish between transient ischemic and heart-rate related ST segment episodes. The ST segment deviation change is higher in ischemic episodes and the ST segment slope change is higher in heart-rate related episodes. The ST segment shape changes more in ischemic episodes. The change of the first Legendre coefficient represents the change of the ST segment deviation and is higher in ischemic episodes. The change of the second coefficient, represents the change of the ST segment slope and is similar in both types of episodes as well. The change of the third coefficient represents the scooping of the ST segment and is not significant.

2.12 Detection Of The QRS Complex, P Wave And T Wave In Electrocardiogram

K. F. Tan, et. al proposed two QRS detection methods are studied. The first method, the "So and Chan" method, is based on the maximum slope detection with the QRS onset selected when two successive values of the slope exceed the threshold. The second method is developed by Pan and Tompkins. American Heart Association (AHA) ECG data files are used to test these two QRS detection methods. Our results show that the "So and Chan" method performs better than the "Pan and Tompkins" method. Further development continues on the "So and Chan" method. This is due both to lower false positive and false negative results. Based on the information of the identified QRS

complexes, the P waves and the T waves are also be detected. However, in some circumstances, the detected T wave in the previous beat is overlapped with the P wave in the current beat. Therefore, the autocorrelation approach to ECG classification is carried out using only the information of the QRS complex.

2.13 Adaptive ECG Filtering And QRS Detection Using Orthogonal Wavelet Transform.

Alice de Jesus Kozakevicius, et. al presented an orthogonal wavelets to filter and analyse ECG signals. First, they used compactly supported wavelets associated to the statistical Stein's Unbiased Risk Estimator (SURE) in order to obtain an adaptive thresholding strategy to filter ECG signals. Second, the filtered signals are analyzed by using the Haar wavelet transform in order to detect the positions of the occurrence of the QRS complex during the period of analysis. Through the SURE adaptive wavelet thresholding all irrelevant noise are removed of the signal, allowing the utilization of a simple wavelet transform in the QRS detection. The main advantage of this kind of detection is a less time consuming analysis for long time ECG signal.

2.14 An Automated System for On-line Monitoring and Detection of ST Changes in ECG Signal.

M. Mohebbi, et. al presented a new automated system for on-line monitoring and detection of ST changes in one channel electrocardiograms (ECG). This system consists of a preprocessing step for QRS detection, baseline wandering removal, and noise suppression. In the next step, the system uses a normal beat template as reference and a set of rules defined by cardiologists for detecting ischemic beats based on ST slope/deviation measurements. In the third step, the system uses a window classification for detecting sequences of ischemic beats. In the final step ischemic episodes in ECG signal are detected by merging sequences which are close together. The performance of the system was evaluated using a subset of ESC ST-T database including 48 records. This evaluation demonstrated high sensitivity (94.5%) and good positive predictivity (85.03%) of our system**.** Short processing time and acceptable accuracy of the proposed method,

are its main advantages and enable it to be used in real time ischemic episodes detection systems and reliable clinical monitoring of the patient status.

CHAPTER-3

Problem Definition

The most important ECG change caused by myocardia1 ischemia is the ST segment change. Elevation and depression of the ST segment together with the T-wave changes indicate the zone of ischaemia around the applied lead. Therefore, to identify the ST segment is the most important feature of the ECG for investigating myocardial ischaemia. One of the ways to identify ischemia is to compare the level of ST segment with the isoelectric line level. Isoelectric line is that potential potential which is recorded by ECG machine when there is no cardiac activity. Generally, it is defined as the flat parts of the EKG that is between the P wave and the QRS complex .

Therefore, to compare these two levels(ST segment level and isoelectric line level) ,it is essential that PQ segment and ST segment to be identified which further requires the identification of QRS complex. The objective of the work is to identify QRS complex, isoelectric line and its level and ST segment and its level.

CHAPTER-4

Problem Solution And Implementation

4.1 Overview

The detection of ST segment deviation is the most important task in detection of ischemia. Several mathematical transforms have been applied to the ECG for ischemia detection such as the discrete cosine transform (DCT), the discrete Fourier transform (DFT), the Karhunen-Loève transform (KLT) and wavelet transform . Other techniques such as artificial neural networks, fuzzy-logic and rule-based have been also proposed literature for ST segment deviation detection. In this , we describe a technique for automatic detection of ST segment deviations that can be used in the diagnosis of coronary heart disease (CHD) using ambulatory electrocardiogram (ECG) recordings. We are presenting a very simple algorithm based on Haar wavelet coefficients to detect QRS complex positions and then determine the ST segment's relative level with respect to isoelectric level which is later used for ischemia detection.

The algorithm should take (at least) the following into account:

- Preprocessing
- QRS detection
- Detection of isoelectric level
- Detection of ST segment level
- Comparison of amplitudes

4.2 MATLAB Simulink

MATLAB is a high-level technical computing language and interactive environment for algorithm development, data visualization, data analysis, and numeric computation. Using the MATLAB product, you can solve technical computing problems faster than with traditional programming languages, such as C, C++, and Fortran.

You can use MATLAB in a wide range of applications, including signal and image processing, communications, control design, test and measurement, financial modeling and analysis, and computational biology. Add-on toolboxes (collections of special-purpose MATLAB functions, available separately) extend the MATLAB environment to solve particular classes of problems in these application areas.

MATLAB provides a number of features for documenting and sharing your work. You can integrate your MATLAB code with other languages and applications, and distribute your MATLAB algorithms and applications.

4.2.1 Key Features

- High-level language for technical computing
- Development environment for managing code, files, and data
- Interactive tools for iterative exploration, design, and problem solving
- Mathematical functions for linear algebra, statistics, Fourier analysis, filtering, optimization, and numerical integration
- 2-D and 3-D graphics functions for visualizing data
- Tools for building custom graphical user interfaces
- Functions for integrating MATLAB based algorithms with external applications and languages, such as C, C++, Fortran, Java, COM, and Microsoft Excel

4.3 Database

The Long-Term ST Database (LTST DB) contains 86 2- or 3-lead 24-hour ambulatory ECG records, sampled at 250 samples s^{-1} per channel, and is intended for development and testing of automatic ischemia detectors. The records were collected during routine clinical practice to model significant number of real-world clinical conditions. During development of the LTST DB, a considerable preprocessing phase took place in order to derive a number of time series of diagnostic and morphologic parameters. The goals of the LTST DB are:

(a) more adequately to represent the wide variety of realworld data that typically challenge real-time automatic ischaemia detectors. The database should include a meaningful number of:

_ transient ST segment episodes compatible with ischaemia (ischaemic ST episodes)

_ non-ischaemic ST episodes due to changes in heart rate (heart-rate related ST episodes)

_ non-ischaemic slow ST segment drifts

_ non-ischaemic ST shifts due to postural changes (axis shifts)

_ non-ischaemic ST shifts due to changes in ventricular conduction (conduction changes)

_ data corrupted by noise and artifacts

(b) to provide sufficient data in each record adequately to represent a variety of characteristic temporal patterns and

dynamics of episodic ischaemia

(c) to include a variety of arrhythmias to support studies on their possible correlations with transient ischaemia.

4.4 Methodology

4.4.1 Preprocessing

In first stage, preprocessing of ECG recording is carried out prior to the extraction of the ST segment which involves removal of noise and rejection of artifact. The standard least-square polynomial curve-fitting technique has been used. This is done in order to avoid the step line quantization error so that the reconstructed signal is acceptable to the physician. In the present work, effect of the use of different standard least-square polynomial curve fitting techniques is considered in detail.

4.4.1.1 Least Square Polynomial Smoothing Filter

This family of finite impulse response filters, fits a parabola to an odd number ($2L + 1$) of input data points in a least-square sense (L is an integer). Figure(3.1a) shows that the output of the filter is the midpoint of the parabola. Writing the equation for a parabola at each point, we obtain:

$p(nT+kT) = a(nT) + b(nT).k + c(nT).k^2$ where k ranges from –L to +L.

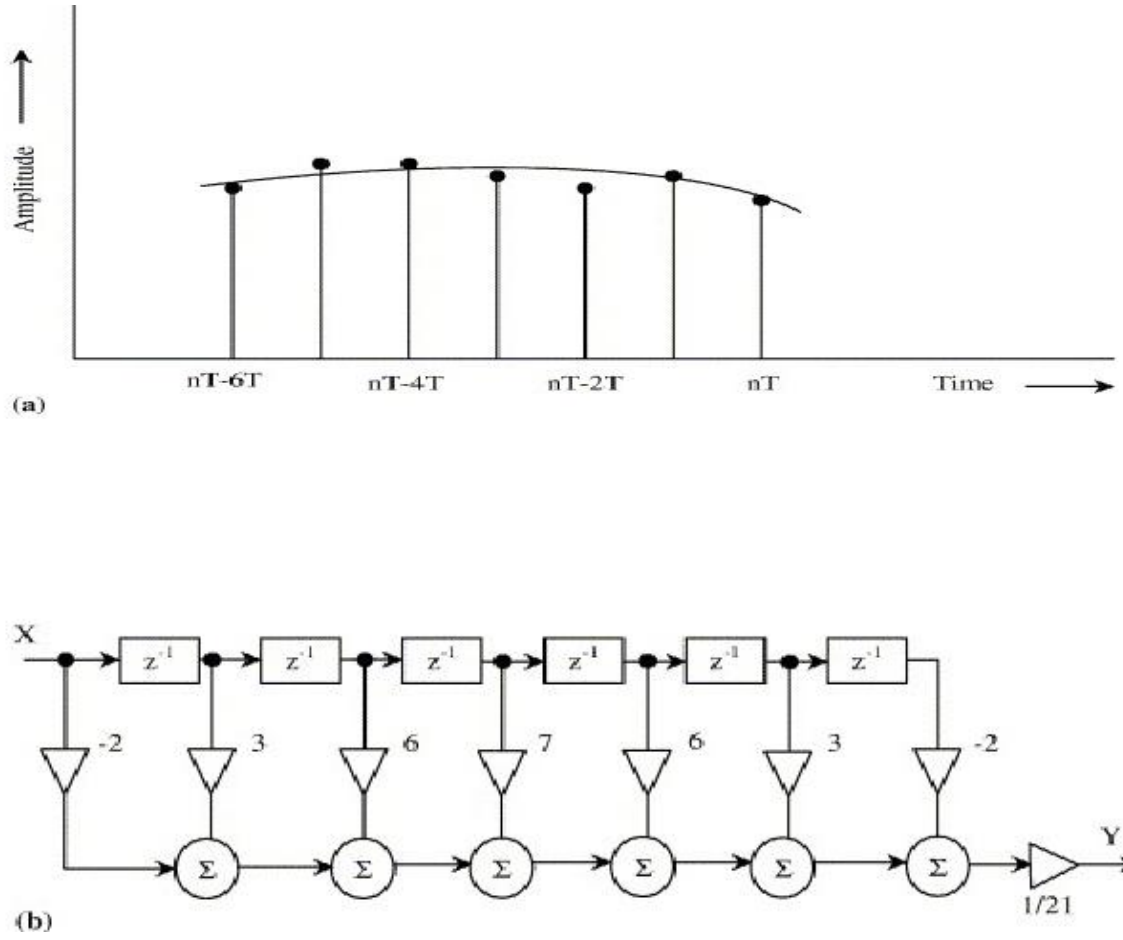


Fig4.1(a) Parabolic fitting of groups of seven sampled datapoints. (b) Signal flow graph

The fit is found by selecting $a(nT)$, $b(nT)$ and $c(nT)$ to minimize the squared error between parabola and input data. Setting the partial-derivatives of the error with respect to $a(nT)$, $b(nT)$ and $c(nT)$ equal to zero results in a set of simultaneous equations in $a(nT)$, $b(nT)$, $c(nT)$, k and $p(nT - kT)$. Solving to obtain an expression for $a(nT)$, the value of the parabola at $k = 0$ yields an expression, a function of the input values. The coefficients of this expression are the tap weights for the least-square polynomial filter as shown in the signal flow graph of figure(4.1b) for a 7-point filter.

The difference equation for the 7-point parabolic filter is:

$$H(z) = 1/21[-2 + 3z^{-1} + 6z^{-2} + 7z^{-3} + 6z^{-4} + 3z^{-5} + -2z^{-6}]$$

4.4.1.1(a) Original ECG Signal

For ECG signal plot in MATLAB:

```
>>  plot (origsignal);
>> title ('original signal');
>> xlabel ('time');
>> ylabel ('amplitude');
```

plot(origsignal) plots the columns of 'origsignal' versus their index if 'origsignal' is a real number.

title ('original signal') outputs the string at the top and in the center of the current axes.

xlabel ('time') labels the x-axis of the current axes.

ylabel ('amplitude') labels the y-axis of the current axis.

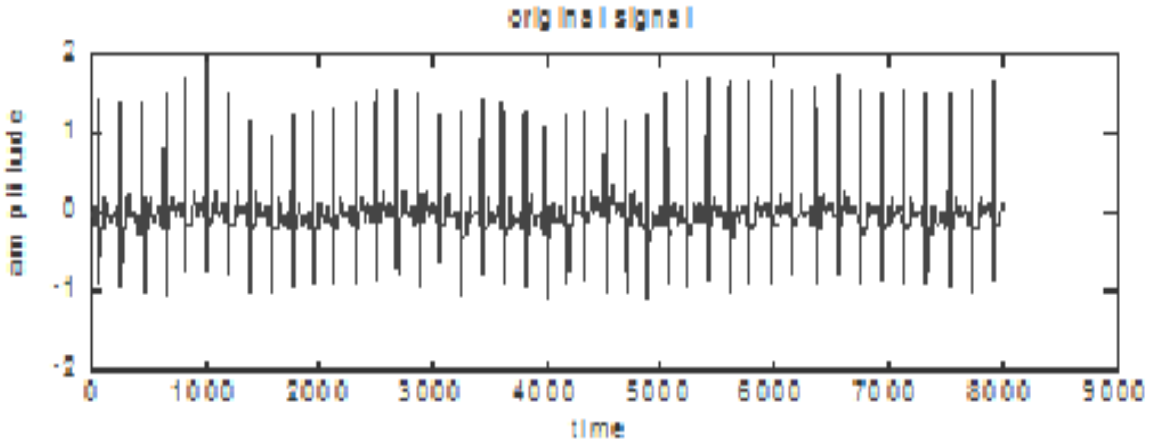


Fig 4.2 Original ECG data plot

4.4.1.1(b) Denoised ECG Signal

Implementation of seven-point parabolic filter in MATLAB:

```
>>filtsignal=m(n)*7+m(n-1)*6+m(n-2)*3+m(n-3)*-2+m(n+1)*6+m(n+2)*3+m(n+3)*(-
2);
>>denois(n) = filtsignal/21;
>>subplot(2,1,2); plot(denois);
>>title('denoised signal');
```

>>xlabel('t');

>>ylabel('a');

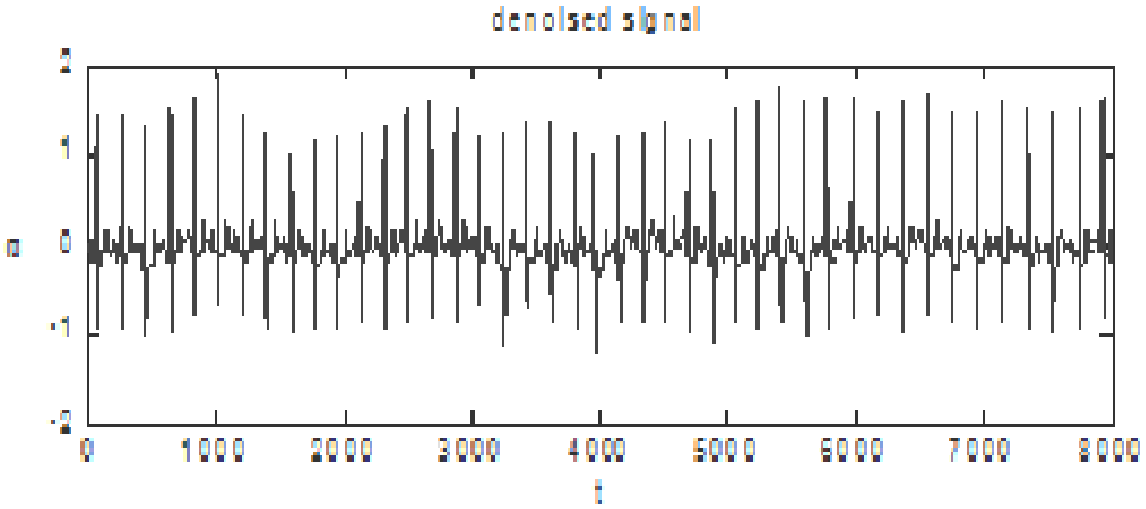


Fig4.3 Filtered ECG signal using seven point parabolic filter

4.4.2 QRS Detection

The QRS complex duration is another important parameter employed in the analysis and classification of the ECG signal. Because all other features, like the P and T waves and the on- and offset of the QRS complex are defined relative to the QRS complex. This parameter is defined as the time it takes for depolarization of the ventricles. Normal depolarization requires normal functioning of the right and left bundle branches and it varies from 0.04 to 0.09 seconds. Any block in either the right or left bundle branch delays depolarization of the ventricle due to the blocked bundle. In abnormal cases the QRS interval is 0.1 seconds or more. There is an intraventricular conduction delay when the QRS interval is between 0.1 to 0.12 seconds. QRS intervals greater than 0.12 seconds indicate bundle branch block .

In this section a simpler method is proposed, based on Haar transform, to obtain a lightweight detection algorithm. On this algorithm, P and T waves are not detected, since it is focused on counting and localizing abnormal QRS patterns for long time ECG analysis. After we filtered the signal with the seven-point parabolic filter, Haar wavelet transform is applied in order to capture small scale variations, which are intrinsic to the

signal. These variations will localize the QRS complex in each scale. Even in abnormal cases, this behaviour is observed.

The following algorithm summarizes the procedure for detecting QRS localization through Daubechie wavelet coefficients:

1. Apply Daubechie wavelets of order 1 on ECG in j levels;
2. Find the maximum wavelet coefficient for each level (max(cDj));
3. For each level select the details (cD *j,i*) associated to QRS complex using $\beta_1 = 0.5$ (a weight of max (cD *j*)):

   if $|cD_{j,i}| > \beta_1 \max(cD_j)$ { then position i ϵ QRS complex; else position i ∉ QRS complex

4. Identify different QRS complexes: cD*j,i* and cD *j,i'* are consecutive selective coefficients; $\beta_2 = 0.1$ is 0.1*(standard QRS time duration);

   $\Delta t = 1/f = 0.0005$;

   if $(t = 2^j \Delta t |i - i'| < \beta_2$ { then i, i' ϵ same QRS complex; else i, i' ∉ same QRS complex

4.4.2.1 Discrete Wavelet Transform

A discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency and location information . it converts an input series x_0, x_1, ..x_m, into one high-pass wavelet coefficient series and one low-pass wavelet coefficient series (of length n/2 each) given by:

$$H_i = \sum_{m=0}^{k-1} x_{2i-m} \cdot s_m \quad (z) \qquad (1)$$

$$L_i = \sum_{m=0}^{k-1} x_{2i-m} \cdot s_m \, (z) \qquad (2)$$

where $s_m(Z)$ and $t_m(Z)$ are called wavelet filters, K is the length of the filter, and i=0, ..., [n/2]-1.

The DWT is computed by successive lowpass and highpass filtering of the discrete time-domain signal as shown in figure 2.2. This is called the Mallat algorithm or Mallat-tree decomposition. Its significance is in the manner it connects the continuous-time mutiresolution to discrete-time filters. In the figure, the signal is denoted by the sequence x[n], where n is an integer. The low pass filter is denoted by G_0 while the high pass filter is denoted by H_0. At each level, the high pass filter produces detail information, d[n], while the low pass filter associated with scaling function produces coarse approximations, a[n].

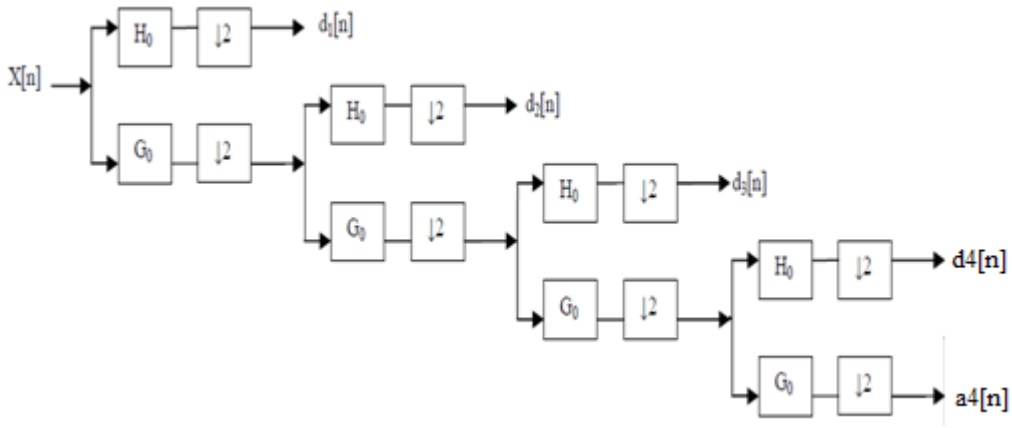


Fig4.4.Four level wavelet decomposition tree

At each decomposition level, the half band filters produce signals spanning only half the frequency band. This doubles the frequency resolution as the uncertainity in frequency is reduced by half. In accordance with Nyquist's rule if the original signal has a highest frequency of ω, which requires a sampling frequency of 2ω radians, then it now has a highest frequency of ω/2 radians. It can now be sampled at a frequency of ω radians thus discarding half the samples with no loss of information. This decimation by 2 halves the time resolution as the entire signal is now represented by only half the number of samples. Thus, while the half band low pass filtering removes half of the frequencies and thus halves the resolution, the decimation by 2 doubles the scale. The choice of the wavelet function depends on the application. The Haar wavelet algorithm has the advantage of being simple to compute and easy to understand. The Daubechies algorithm is conceptually more complex and has a slightly higher computational overhead. But, the Daubechies algorithm picks up detail that is missed by the Haar wavelet algorithm. Even

if a signal is not well represented by one member of the Db family, it may still be efficiently represented by another. Selecting a wavelet function which closely matches the signal to be processed is of utmost importance in wavelet applications.

To make a 4-level wavelet decomposition of a signal m with Daubechie wavelets of order 1(db1) using the command line tools you write

>> [C,L] = wavedec(m,4,'db1');

The coefficients of all the components of a fourth-level decomposition (that is, the four-level approximation and the first four levels of detail) are returned concatenated into one vector, C. Vector L gives the lengths of each component.

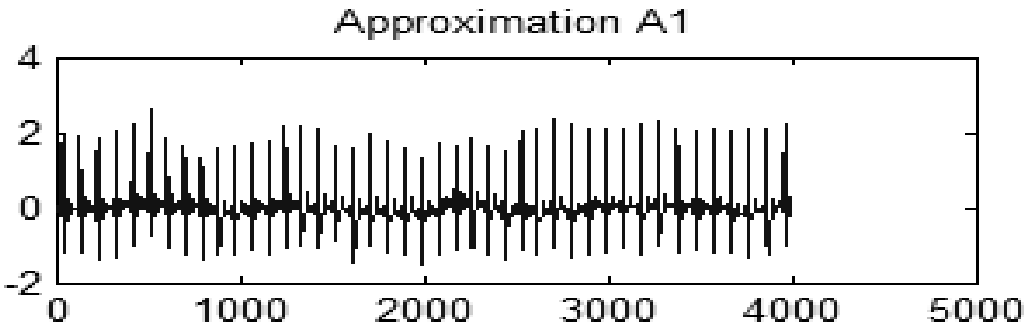
To extract the level 4 approximation coefficients from C, type

>>cA1 = appcoef(C,L,'db1',1);

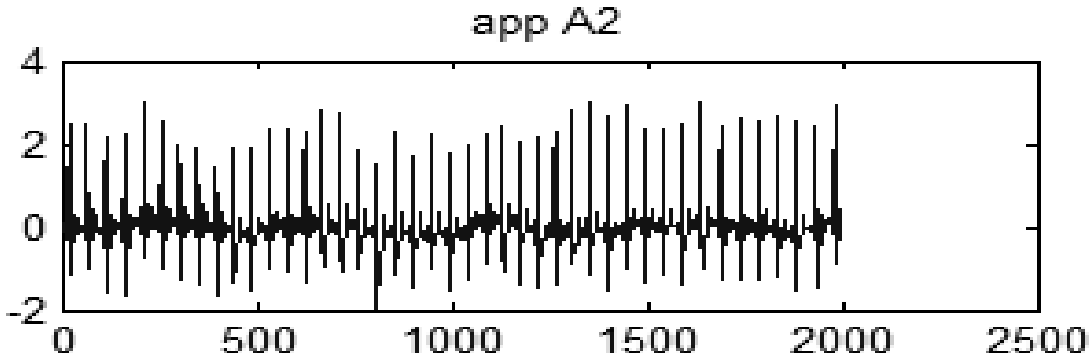
>>cA2 = appcoef(C,L,'db1',2);

>>cA3 = appcoef(C,L,'db1',3);

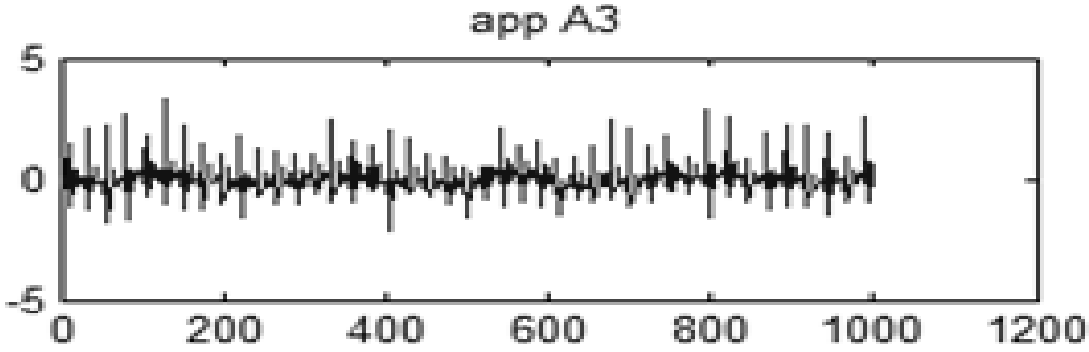
>>cA4=appcoef(C,L,'db1',4);



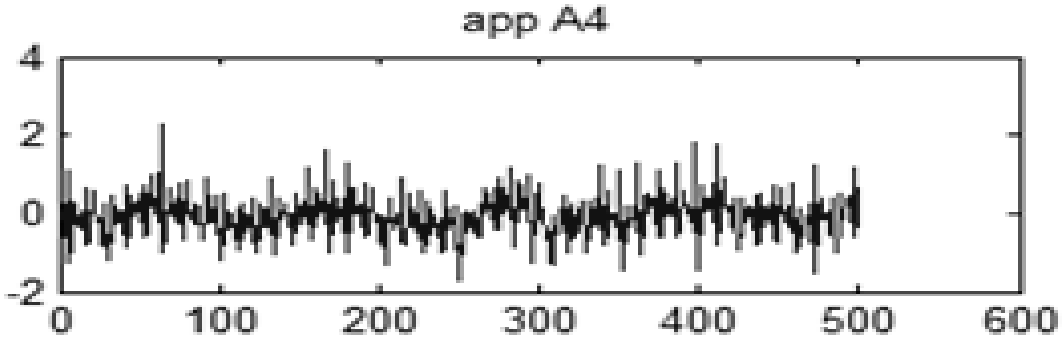
(a)



(b)



(c)



(d)

Fig4.5.(a)Level1 approximation coefficient, (b)Level2 approximation coefficient,(c)Level3 approximation coefficient, (d) Level4 approximation coefficient.

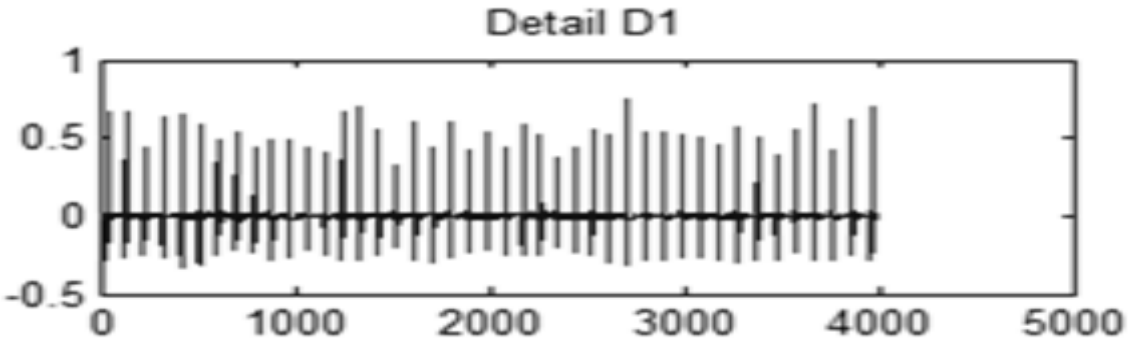
To extract the levels 4,3, 2, and 1 detail coefficients from C, type

>>cD1 = detcoef(C,L,1);

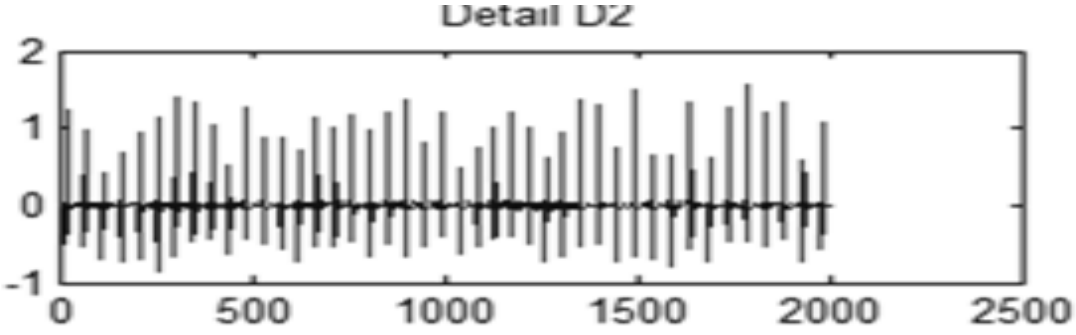
>>cD2 = detcoef(C,L,2);

>>cD3 = detcoef(C,L,3);

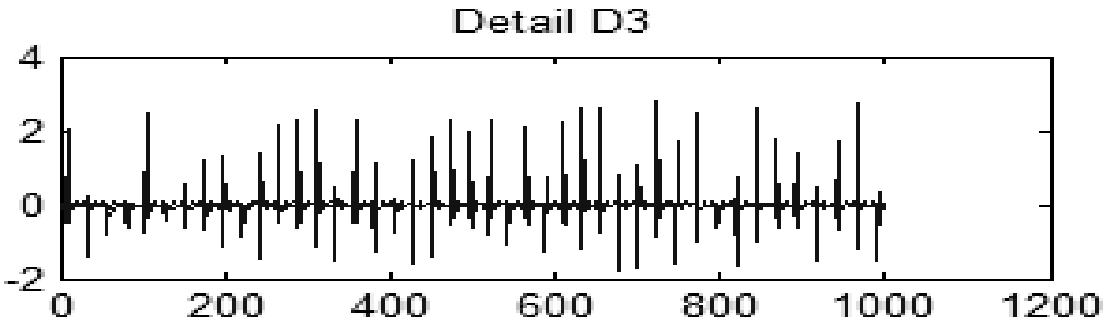
>>cD4 = detcoef(C,L,4);



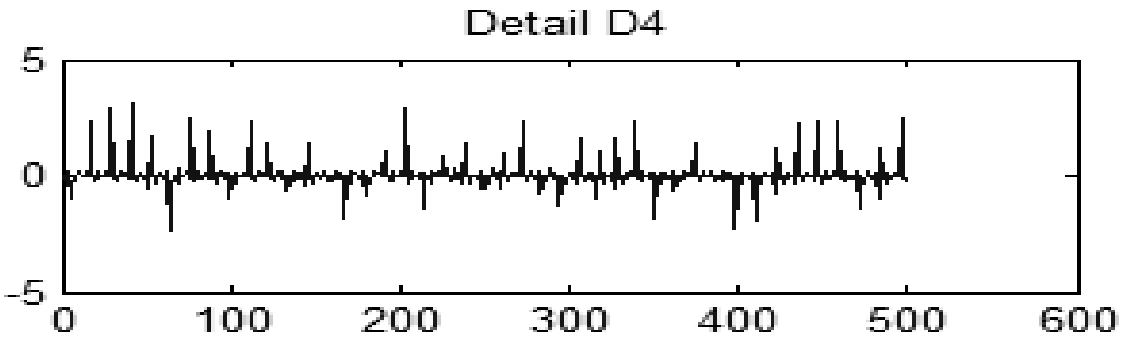
(a)



(b)



(c)



(d)

Fig4.6.(a)Level1 detail coefficients, (b) Level 2 detail coefficients,(c) Level 3 detail coefficients, (d) Level 4 detail coefficients

1. Find the maximum wavelet coefficient for each level (max(cDj));

MATLAB code for this is given below:

```
>> absval1=abs(cD1)
>> absval2=abs(cD2)
>> absval3=abs(cD3)
>> absval4=abs(cD4)
>> absval5=abs(cD5)
>> max1 = max(absval1)
>> max2 = max(absval2)
>> max3 = max(absval3)
>> max4 = max(absval4)
```

absvalj= abs(cDj) returns the absolute value of object cDj with same numeric type.

maxj = max(absvalj) returns the maximum value along different dimensions of an array.

2. For each level select the details (cD *j,i*) associated to QRS complex using β_1 = 0.5 (a weight of max (cD *j*)):

MATLAB code for this is given below:

```
>> detail1=max1/2
>>detail2=max2/2
>>detail3=max3/2
>>detail4=max4/2
```

```
>>len1=length(absval1);
>>k=1;
>>for loop1=1:len1
>>        if(absval1(loop1)>deatil1)
>>        mat1(k)=2*loop1;
>>        k=k+1;
>>        else
>>       end;
>> end
>> len2=length(absval2);
>> k=1;
>> for loop2=1:len2
>>        if(absval2(loop2)>detail2)
>>        mat2(k)= 4*loop2;
>>        k=k+1;
>>        else
>>       end;
>> end
>> len3=length(absval3)
>> k=1;
>> for loop3=1:len3
>>        if(absval3(loop3)>detail3)
>>         mat3(k)=8*loop3;
>>         k=k+1;
>>         else
>>        end;
>> end

>> len4=length(absval4);
 >>k=1;
>> for loop4=1:len4
```

```
>>      if(absval4(loop4)>detail4)
>>      mat4(k)=16*loop4;
>>      k=k+1;
>>      else
>>      end;
>> end
```

The position of above calculated matrix values in mat1,mat2,mat3,mat4 belong to QRS complex.

3. Identify different QRS complexes: cD*j,i* and cD *j,i'* are consecutive selective coefficients; $\beta_2 = 0.1$ is 0.1*(standard QRS time duration)

MATLAB code for peak identification is given by:

```
>> newdata = [mat1 mat2 mat3 mat4];
>> sortdata = sort(newdata);
>> lendata=length(sortdata);
>> s=1;
>> for t=1:(lendata-1)
>>    diff = sortdata(t+1)-sortdata(t);
>>    if (diff<10)
>>       limit1(s)=sortdata(t);
>>       s=s+1;
>>    else
>>       break;
>>    end;
>> end
>> r=length(limit1);
>> k=1;
>> for i=limit1(1):limit1(r)
>>    peakdet(k)=abs(denois(i));
>>    k=k+1;
>> end
```

```
>> rpeak=max(peakdet);
>> length1=length(peakdet);
>> for x=1:length1
>>     if (peakdet(x)==denois)
>>       peak1=limit1(1)+(x);
>>     end;
>> end
```

With the application of above code to the pairs having difference in their elements less than 10 in the sortdata matrix, the total number of peaks detected were 41 which when visually compared with original data having actually 42 peaks. And no false peak is detected.

4.4.3 Detection of Isoelectric Level

Isoelectric line is the flat parts of the EKG, for example between the T and P waves or between the P wave and the QRS complex. A band selection method is developed for the detection of isoelectric level detection. In this, the results obtained from QRS detection technique i.e: the magnitude of R-peak which is also known as first maxima of the ECG signal.

Firstly, small overlapping bands are chosen between the maxima and minima of QRS peak. Each band is 0.05mV wide and the two consecutive bands are differentiated by 0.1mV.

MATLAB code for this is given by:

```
>> steps = floor((rpeak-peakmin1)/0.05);
>> for n = 1:steps+1
>>     nofpoints(n)=0;
>> end
>> j=1;
>> for w=peakmin1:0.05:rpeak
>>     for i=1:length(isomat)-1
>>       if (isomat(i)>w)&&(isomat(i)<(w+0.1))
```

```
>>         nofpoints(j)=nofpoints(j)+1;
>>       end;
>>     end
>>   j=j+1;
>> end
```

After the selection of bands, the population in each band upto 50 points to the left of maxima is calculated using MATLAB coding. The band having maximum population of points is considered as the most probable band and this is resulted as isoelectric line.

MATLAB code for this is given by:

```
>> isoband = max(nofpoints);
>> for j=1:steps
>>    if (nofpoints(j)==isoband)
>>       isoline=j;
>>       lim_upper=(peakmin1+0.05*(isoline-1)+0.1);
>>       lim_lower=(peakmin1+0.05*(isoline-1));
>>    end;
>> end
```

After getting the limits of most probable band, isoelectric level is calculated by averaging the points in this band and the result gives the level of isoelectric line and this level is later used for comparison with ST segment level.

MATLAB code for isoelectric level detection is given by:

```
>> r=1;
>> for pt=1:length(m)-1
>>    if (isomat(pt)<lim_upper)&&(isomat(pt)>lim_lower)
>>       isomat(r)=isomat(pt);
>>       r=r+1;
>>       isosum= sum(isomat);
>>       isoavg=isosum/isoband;
>>    end;
```

```
>> end
```

The average level comes out to be -0.135mV which is the amplitude of isoelectric line which when subtracted from ST segment level gives the deviation of ST segment.

4.4.4 Detection of ST segment level

The ST segment is the most important feature of the ECG for investigating myocardial ischaemia. The ST interval is measured from the J point to the end of the T wave. The elevation and depression of ST segment together with the T-wave changes indicate the zone of ischaemia around the applied lead.

A similar method is developed for the detection of ST segment level. In this method the small overlapping bands are chosen between the maxima and minima of QRS peak which is detected by QRS detection method. Each selected band is 0.05mV wide and two consecutive bands are diffentiated by 0.01mV.

MATLAB code for this is given by:

```
>> ststeps = floor((rpeak-peakmin1)/0.05);
>> for n = 1:steps+1
>>    stnofpoints(n)=0;
>> end
>> p=1;
>> for v=peakmin2:0.05:peak2
>>     for i=1:length(stmat)-1
>>       if (stmat(i)>v)&&(stmat(i)<(v+0.1))
>>          stnofpoints(p)=stnofpoints(p)+1;
>>       end;
>>     end
>>   p=p+1;
>> end
```

After the selction of bands, the population in each selected band upto 50 points to the right of maxima is calculated using MATLAB coding. The band having maximum

population of points is considered as the most probable band and this is resulted as the ST segment.

MATLAB code for this is given by:

```
>> stband = max(stnofpoints);
>> for p=1:steps
>>    if (stnofpoints(p)==stband)
>>       stseg=p;
>>       lim_upper_st=(peakmin1+0.05*(stseg-1)+0.1);
>>       lim_lower_st=(peakmin1+0.05*(stseg-1));
>>    end;
>> end
```

After getting the limits of ST segment band, ST segment level is calculated by averaging the points in this band and the result gives the level of ST segment and this level is used for ischaemia detection.

MATLAB code for ST segment level detection is given by:

```
>> r=1;
>> for pt=1:length(stmat)-1
>>    if (stmat(pt)<lim_upper_st)&&(stmat(pt)>lim_lower_st)
>>      stmat(r)=stmat(pt);
>>       r=r+1;
>>       stsum= sum(stmat);
>>       stavg=stsum/stband;
>>    end;
>> end
```

From the above implementation, it is seen that the average value comes out to be -0.22mV which is considered as the ST segment amplitude.

4.4.5 Comparison of amplitudes of Isoelectric line and ST segment

The last step in the algorithm is to compare the ST segment level with the isoelectric line level. If this segment is significantly below the isoelectric line it is called ST segment depression and it suggests that part of the subject's myocardium is not getting enough oxygen (myocardial ischema). This segment is also frequently elevated (ST segment elevation) above the isoelectric line in the early stages of a myocardial infarction. When ST deviation is more than 0.08 mV below the isoelectric line and has an angle larger than 65degree measured from vertical line, it is considered as negative ST deviation or ST depression. The second rule classifies beat as ischemic if ST deviation is more than 0.08 mv above the isoelectric line which is considered as ST elevation.

Consider the results obtained from isoelectric line and ST segment level detection method which are:

isoavg= -0.135mV and stavg= -0.22mV

When subtracted gives the result -0.085mV which shows that ST segment is deviated below the isoelectric line and hence it is considered as ST depression or negative ST deviation.

CHAPTER-5

Results And Discussion

Ischemia is a state of heart where supply of blood to heart is obstructed. As a result, if this status is prolonged, this may result in dying of some of the cells which is also known as necrosis. This ultimately may lead to heart attack that is also called Myocardial Infarction. Given the importance of ischemia, it is important that we detect its presence at an early stage. Many researchers have worked on detection of ischemia and knowing the features of ECG, ischemia can be detected. It has been reported by many researchers that one of the important parameter of detecting ischemia is by knowing the level of ST segment. In most of the ischemic cases, the ST segment is either elevated or depressed. This elevation or depression of ST segment is taken with respect to isoelectric line.

Table-5.1 Reports the actual and detected number of peaks

Age/Sex	Data Number	No.Of Peaks		FALSE	FALSE
		Actual	Detected	Positive	Negative
58M	20011	35	35	0	0
55M	20031	39	39	0	0
60M	20041	32	31	2	1
87F	20051	63	63	2	0
62F	20101	36	36	1	0
64M	20111	46	45	2	1
48F	20121	31	31	2	0
82F	20131	42	41	1	1
62M	20151	32	32	0	0
65M	20161	32	32	0	0
44M	20171	44	43	2	1
66M	20181	46	43	0	3
57M	20221	50	49	2	1
Undefined	20261	38	38	0	0
		566	558		

We define isoelectric line as the kind of level of ECG when there is no cardiac output and normally it is defined as the level between the end of P-wave and start of QRS complex. To establish the cases as ischemic, it is important that we understand the relative levels of ST segment and that of isoelectric line. The important thing in this case becomes that we detect both isoelectric line as well as the ST segment. As these two segments are

occurring immediately before and immediately after the QRS complex respectively, one of the important steps in identifying the isoelectric line and ST segment line is to identify QRS complex. In this research work, we have to start with detected QRS complexes in large number of samples. Table-5.1 reported that algorithm which we have used using wavelet transforms gives us the accuracy of 98.5% and having identified.

Next aspect was to know the relative position of ST segment and isoelectric line. Isoelectric line was taken as the most probable voltage level for fifty samples before QRS complex at the rate of 250samples per second. Similarly, ST segment is taken as the most probable level for fifty samples after QRS complex. Having found the relative levels, we take the ST segment to be elevated if it is 0.08mV above the isoelectric line and depressed if it is 0.08mV below the isoelectric line otherwise it is taken as normal. The result using this algorithm was compared with the visual inspection and is tabulated below. We have taken 32seconds data from patient number s20101 and s20041 with 8000samples having sampling frequency 250samples per second.

Table-5.2 Reports the relative position of ST segment w.r.t isoelectric line(LTSTDB_s20101)

Database	**Age/Sex**	**Data**
used	**62/F**	**20101**
LTST-DB	**By Visual Check**	**By Computer Algorithm**
Peak 1	Elevated	Elevated
Peak 2	Normal	Normal
Peak 3	Normal	Normal
Peak 4	Normal	Normal
Peak 5	Normal	Normal
Peak 6	Elevated	Elevated
Peak 7	Depressed	Depressed
Peak 8	Depressed	Depressed
Peak 9	Depressed	Depressed
Peak 10	Depressed	Depressed
Peak 11	Normal	Normal
Peak 12	Depressed	Normal
Peak 13	Normal	Normal
Peak 14	Depressed	Depressed
Peak 15	Depressed	Depressed
Peak 16	Depressed	Depressed
Peak 17	Depressed	Depressed
Peak 18	Depressed	Depressed
Peak 19	Depressed	Depressed

Peak 20	Depressed	Depressed
Peak 21	Depressed	Depressed
Peak 22	Normal	Normal
Peak 23	Normal	Normal
Peak 24	Depressed	Depressed
Peak 25	Normal	Normal
Peak 26	Depressed	Depressed
Peak 27	Depressed	Depressed
Peak 28	Depressed	Depressed
Peak 29	Normal	Normal
Peak 30	Depressed	Depressed
Peak 31	Depressed	Depressed
Peak 32	Normal	Normal
Peak 33	Normal	Normal
Peak 34	Normal	Normal
Peak 35	Normal	Normal
Peak 36	Normal	Normal

Table-5.3 Reports the relative position of ST segment w.r.t isoelectric line(LTSTDB_s20041)

Database used	**Age/Sex 62/F**	**Data 20041**
LTST-DB	**By Visual Inspection**	**By Computer Algorithm**
Peak 1	Depressed	Depressed
Peak 2	Depressed	Normal
Peak 3	Depressed	Depressed
Peak 4	Depressed	Depressed
Peak 5	Depressed	Depressed
Peak 6	Depressed	Depressed
Peak 7	Depressed	Depressed
Peak 8	Depressed	Depressed
Peak 9	Depressed	Depressed
Peak 10	Depressed	Depressed
Peak 11	Depressed	Depressed
Peak 12	Depressed	Normal
Peak 13	Depressed	Depressed
Peak 14	Depressed	Depressed
Peak 15	Depressed	Depressed
Peak 16	Depressed	Depressed
Peak 17	Depressed	Depressed
Peak 18	Depressed	Depressed
Peak 19	Depressed	Depressed
Peak 20	Depressed	Depressed
Peak 21	Depressed	Depressed
Peak 22	Depressed	Depressed
Peak 23	Depressed	Depressed
Peak 24	Depressed	Depressed
Peak 25	Depressed	Depressed

Peak 26	Depressed	Depressed
Peak 27	Depressed	Depressed
Peak 28	Depressed	Depressed
Peak 29	Depressed	Depressed
Peak 30	Depressed	Depressed
Peak 31	Depressed	Depressed

Table-5.4 Comparison of results calculated using algorithm with visual inspection

Age/Sex	Database LTSTDB	Peaks Detected					
		By Visual Inspection			By Computer Algorithm		
	Data No.	Elevated	Depressed	Normal	Elevated	Depressed	Normal
58M	20011	0	35	0	0	35	0
62F	20101	2	18	16	2	19	15
60M	20041	0	32	0	0	29	2
55M	20031	39	0	0	39	0	0
64M	20111	5	30	11	5	27	13
48F	20121	0	31	0	0	29	2
62M	20151	32	0	0	32	0	0
82F	20131	0	37	5	0	35	6
65M	20161	32	0	0	32	0	0
44M	20171	0	36	8	0	33	10
57M	20221	0	50	0	0	47	2
Undefined	20261	0	38	0	0	38	0
66M	20181	35	7	4	35	5	3
87F	20051	0	63	0	0	61	2

Reasonable amount of accuracy can be seen in the tables.

CHAPTER-6

Conclusion and Future Scope

6.1 Conclusion

Different researchers used different methods to calculate the ST segment level but in this present work we presented an algorithm that QRS complex on time axis. Detection of QRS complex is done by Wavelet Transforms. We found that there is reasonable amount of accuracy given by 98.5% which can be seen in the tables and it can be therefore concluded that the algorithm which have proposed can be used for most of the practical purposes.

6.2 Future Scope

In this present work, we have done the analysis with 14 subjects and for the short term recording of ECG data samples i.e. 32 seconds. The results obtained are satisfactory but the overall accuracy is not 100%, it is 98.5%. The database used is Long Term ST Database. For the more precise results this work can be extended with more number of subjects and with different database.

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