Detection of Angina Pectoris Using ECG Signals

By

(Md. Merajul Islam)

A project submitted in partial fulfillment of the requirement for the degree of

Master of Science in Biomedical Engineering

Khulna University of Engineering & Technology (KUET)

Khulna 9203, Bangladesh

June 2018

Declaration

This is to certify that the project work entitled **"Detection of Angina Pectoris Using ECG Signals"** has been carried out by **Md. Merajul Islam** in the Department of Biomedical Engineering, Khulna University of Engineering & Technology (KUET), Khulna, Bangladesh. The above project work or any part of this work has not been submitted anywhere for the award of any degree or diploma.

Signature of Supervisor

Md. Merajul Islam

Signature of Candidate

Approval

This is to certify that the project work submitted by Md. Merajul Islam entitled "Detection of Angina Pectoris using ECG Signal" has been approved by the board of examiners for the partial fulfillment of the requirements for the degree of M. Sc. Engineering in the Department of Biomedical Engineering, Khulna University of Engineering & Technology (KUET), Khulna, Bangladesh in June 2018.

BOARD OF EXAMINERS

1. _____ 27.06.18 — Chairman (Supervisor)
Prof. Dr. A. B. M. Aowlad Hossain
Dept. of Electronics and Communication Engineering (ECE)
Khulna University of Engineering & Technology (KUET)
Khulna-9203, Bangladesh

2. _____ 27/06/18 — Member
Prof. Dr. Md. Nurunnabi Mollah
Head of the Department
Dept. of Biomedical Engineering (BME)
Khulna University of Engineering & Technology (KUET)
Khulna-9203, Bangladesh

3. _____ 27/06/18 — Member
Prof. Dr. Mohiuddin Ahmad
Department of Electrical and Electronic Engineering (EEE)
Khulna University of Engineering & Technology (KUET)
Khulna-9203, Bangladesh

4. _____ 27/06/18 — Member
Prof. Dr. Md. Foisal Hossain
Dept. of Electronics and Communication Engineering (ECE)
Khulna University of Engineering & Technology (KUET)
Khulna-9203, Bangladesh

5. _____ 27.06.18 — Member (External)
Prof. Dr. Mohammad Ismat Kadir
Electronics & Communication Engineering (ECE) Discipline
Khulna University
Khulna-9208, Bangladesh

Dedicated to-

My Parents and Loving Wife

Acknowledgement

In the ending of my project work for M.Sc. Eng. degree, first of all, I am mostly thankful to the Almighty Allah for giving me the strength and confidence to complete it successfully.

In this stage, I would like to thank my graduation committee. It is pleasure to express my deepest sense of gratitude and respect to my honorable thesis advisor, **Prof. Dr. A. B. M. Aowlad Hossain**, Department of Electronics and Communication Engineering (ECE), KUET, who was my inspiration during my project work. His invaluable suggestions, proper guidance, and encouragement helped to finish my work. His activeness, friendly behavior, and motivation were really memorable.

In addition, I wish to express my sincere gratitude to **Prof. Dr. Md. Nurunnabi Mollah,** Head, Department of Biomedical Engineering for giving me many good pieces of advice. It is my pleasure to acknowledge the roles of **Engr. Md. Asadur Rahman,** PhD Candidate, Department of BME who was with me from the beginning of my project work, helped me, and supported me.

Besides, I am very much grateful to my parents and my loving wife those who sacrificed a lot to provide me the freedom to engage with this work. I am grateful to all the BME faculty members, staffs, and postgraduate students who helped me directly or indirectly.

Author

June 2018

Abstract

Angina pectoris due to ischemia is very crucial to detect because, if it can be detected earlier, doctor can provide the patient proper medication to cure. Sometimes from a long ECG data it is tiresome to calculate and differentiate the normal and angina pectoris affected ECG peak to decide about the condition of the patient. In addition, the remote areas of lower and mid-lower income countries often face lack of experienced doctors or highly cost devices like eco-cardiogram, MRI to detect angina. In these regions, automatic identification of ECG features can be a fruitful solution. Therefore, only way is computerized and efficient ECG analyzing algorithm development that can be able to detect angina pectoris. In this work, an efficient algorithm is developed to detect angina pectoris from ECG signal. This algorithm consists of several steps to take decision on ECG signal. First of all this algorithm removes baseline wandering from ECG signal by baseline wandering path finding algorithm. After that it removes other noises from ECG signal by Gaussian weighted moving average window method. In this consequence, QRS complex was detected by very well-known method First and Second Derivative (FS2) algorithm and gradually other important points like S, J, K, and T were detected by possible range maxima-minima criterion. Besides, the isoelectric line of ECG signal is estimated and eventually the statistical features of J-K points of normal and abnormal ECG peaks are compared with that isoelectric line by the algorithm, Finally, this algorithm takes the decision whether the patient is suffering from angina or not. This algorithm is applied on MIT arrhythmia Database to detect angina pectoris. From the result provided by this algorithm, we have found 94% (average) accuracy which is noticeable. In addition with that the sensitivity and specificity of our proposed algorithm have also been calculated which are found 91% and 89%, respectively. Since the previous work is based on the single feature, it may prove inappropriate for all the time. Therefore with the help of multiple features machine learning based approach k-nearest neighbor (kNN) method has been deployed in this research work to make it more accurate and acceptable. Although kNN based prediction method also provide almost similar results found by the previous methodologies. Therefore our proposed approach for angina pectoris detection has been testified by both statistical and kNN based method. It is expected that the proposed algorithm will be helpful for computerized angina pectoris detection from ECG signals.

Contents

List of Tables

List of Figures

List of Abbreviations

Abbreviated Form	Elaboration
A/D	Analog-to-Digital
AFD	Analog Filter Design
AV node	Atrioventricular node
BA	Bayesian Algorithm
BIH	Beth Israel Hospital
BWPF	Baseline Wander Path Finding
CAD	Coronary Artery Disease
CT	Computed Tomography
ECG	Electrocardiography
FN	False Negative
FP	False Positive
FS2	First and Second Derivative 2
GUI	Graphic User Interface
HRV	Heart Rate Variability
IEL	Isoelectric Line
IIR	Infinite Impulse Response
kNN	k Nearest Neighbor
LDA	Linear Discriminant Analysis
MIT	Massachusetts Institute of Technology
MLII	Modified Limb Lead II
MRI	Magnetic Resonance Imaging
NSR	Sinus Rhythm
SA node	Sinoatrial node
TN	True Negative
TP	True Positive

CHAPTER 1: Introduction

1.1 Introduction

Heart diseases are the leading causes to death in the world. The most common for heart disease is myocardial ischemia which is one of the most serious & prevalent heart diseases. According to the report of WHO 2015 [1], ischemic heart disease and stroke are the world's biggest killers which leads to 15 million deaths (54%) in 2015. Myocardial ischemia is very common cardiac disease.

Electrocardiography or ECG signal is a pattern of graphical representation of electrical activity of cardiac system and it is often used to measure the various cardiac diseases and abnormalities of the heart function. The graphical representation of ECG signal consists of P, QRS complex, T wave which is given in Figure 1.1. These waves correspond to the fields induced by specific electric phenomenon on the cardiac surface. Atrial depolarization produces the P wave, ventricular depolarization produces QRS complex and ventricular repolarization produces T wave [2]. Angina pectoris, commonly known as angina, is severe chest pain due to ischemia of the heart muscle, generally due to obstruction or spasm of the coronary arteries. Angina pectoris is of two kinds: stable angina and unstable angina. Stable angina occurs during exertion, can be quickly relieved by resting or taking nitroglycerin, and lasts from three to twenty minutes. On the other hand, 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 which may be a serious indicator of an impending heart attack.

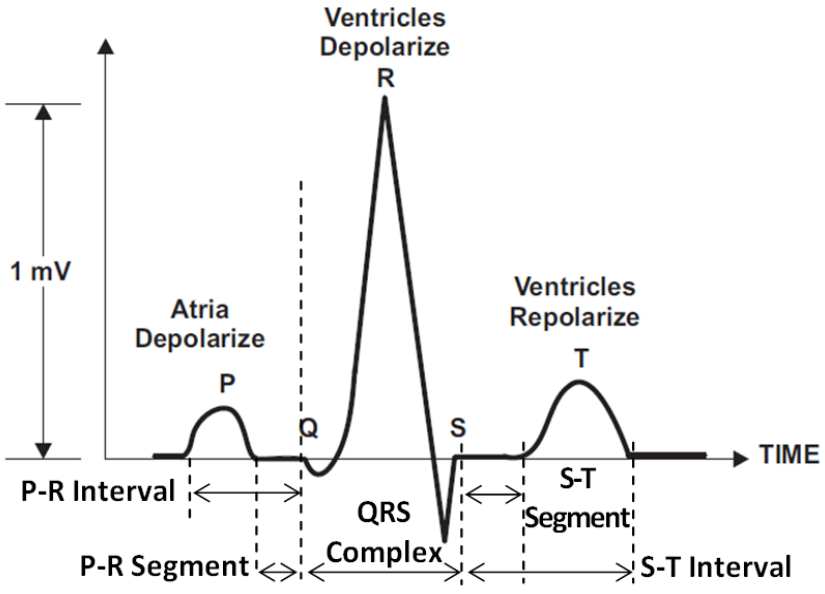


Figure 1.1: A model of ECG signal with its important peaks and interval

The important and common feature of ischemia in the cellular level is the depolarization of the cellular resting membrane potential. As large the 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 ECG. As a result, early detection of heart disease through ECG signal has a vital significance in the medical science which is demanding challenge for the Biomedical Engineers. ECG could be a potential signal of heart that can be applied to find the computerized angina pectoris detection.

1.2 Motivation

People with an average age of 62 years, who have moderate to severe degrees of angina, have a 5-year survival rate of approximately 92% [3]. It is very crucial to detect ischemia because, the effects of myocardial ischemia can be almost reversible if it can be detected early enough [4]. Therefore, the importance of identification of angina pectoris is significant.

There are various invasive and non-invasive modalities for detecting angina pectoris. In recent days [5] the researchers suggested various invasive costly modalities for detecting angina pectoris such as Angiography, Electro-beam CT, multi-detector row CT, Coronary Angiography, Cardiac MRI, Echocardiography, etc. These modalities are very costly which quite impossible for the low or lower-middle income country to effort this service for their remote area patients. The patients of the remote areas of those countries should have some alternative solution for this problem. Beyond the clinically applicable highly costly device, ECG could be an alternative solution for angina detection because due to ischemia ECG features are also significantly changed, mostly the S-T segments.

1.2 Problem Statements and Scopes

Though specificity and sensitivity for detecting cardiac ischemia of aforementioned modalities are comparatively high but these modalities are costly for patients in third world like Bangladesh. Globally, an estimated 54 million people have angina, 16 million of whom are from the South-East Asia region. These modalities are unavailable in most of the remote places for diagnosis of angina pectoris. Electrocardiography is the non-invasive modalities for detecting angina pectoris. It is comparatively cheap and available in remote places. In most of cases it is observed that, doctors of diagnostic center cannot detect the angina pectoris by eyes from long ECG signal due to lack of experiences.

There are several research articles [6]-[11], those proposed methods to detect angina pectoris from ECG signal. These methods are mostly based on machine learning based [6]-[10] or wavelet based [11]. The research work proposed in [6] used PCA based feature extraction method to reduce the dimensionality reduction. This method shows lower classification accuracy. On the other hand, the research work in [7] cannot propose a real computer assisted algorithm for the real classification of ECG beats into angina affected and not affected classes. In [8], authors discussed about the classification optimization of the myocardial affected ECG signal regarding different promising classifiers. Although a deep learning based a complex artificial neural network has been proposed in [9], the accuracy level is lower instead it would be. On the other hand, an overall prediction on ECG signal to find out whether there is any abnormality exists or not has been proposed with the help of artificial neural network in [10]. This article avoids taking decision on beat based feature of ECG signal. A wavelet based feature extraction method proposed in [11] claiming itself an approximately prediction algorithm considering the overall features of ECG signal.

Eventually, from the wide literature review based on the previous works we can reach to an argument that these methods can detect whether the ECG of the patient is angina pectoris affected or not. The dissimilarity between short time angina and chronic angina cannot be differentiated by these methods. These methods cannot count how many affected ECG beats and how many normal ECG are existed in the ECG signal. But these are important for angina pectoris detection. To reach the each peak and their corresponding features should have to explore to take proper decision against the patient. Therefore, the previously mentioned methods can be proved false due to its assumption and there is no scope for a doctor to take decision on the result of the outcomes of these methods. In addition, these methods need to train with a huge number of normal and abnormal ECG data which is also a drawback of these proposed systems

From this view point, there arises a scope to develop an algorithm to detect angina pectoris from ECG signal which will be able to diagnosis of angina pectoris. In this work, an algorithm based on statistical feature is proposed including a number of preprocessing steps like baseline wandering removal, power noise elimination, peak findings, isoelectric line estimation, comparing, etc. Based on a number of features of S-T segment of the each beat of the ECG signals, a predictive model by machine learning algorithm comparing suitable features of the signal beats can be implemented to count how many abnormal ECG beat are there in the testing signal.

1.3 Objectives

The objective of this project is to develop an efficient algorithm that can be able to count the abnormal and normal ECG peaks which leads to decide whether the patient has angina or not.

The specific objectives of the project work are summarized below:

- Collecting necessary ECG data related to angina pectoris and processing the raw signal to remove noises.
- Finding the different peaks for feature extraction
- Extracting Features for effective analysis and classification.
- Classifying whether the ECG data contains angina or not using efficient classifier.
- Investigating the performance and accuracy of the proposed system.

1.4 Thesis Outlines

- **Introduction:** The introductory information about the project work is presented in Chapter 1. In addition, the previous works related to this project has widely examined and their important limitations are reported in this chapter. The objective of this project is also clarified in this chapter.
- **Angina Pectoris and Its Interpretation in ECG:** The basic relation of angina pectoris with the variation of the ECG signal beat pattern has been widely discussed in Chapter 2. The basic functionality of the heart during the effect of angina and the corresponding effect on ECG beat pattern were the main concerning issue of the discussion of this chapter.
- **Methodology:** The technical details of the proposed methodologies of this work are given in Chapter 3. The mathematical background of the peaks of the ECG beat, different filtering criteria, feature extraction methodology, classification techniques, etc. are broadly explained mentioning the relation of this project work.
- **Results and Discussions:** The main outcomes of this project work have been reported in the Chapter 4. The results have been presented in tabular or graphical form with neat and detail discussions.
- **Conclusions:** The total project work has been concluded in Chapter 5. Here, the future perspectives have also been a concerning issue that will help the future researchers to work more efficiently with the task related to this project work.

CHAPTER 2: Angina Pectoris and Its Interpretation in ECG

2.1 Introduction

In this chapter, a broad discussion will be carried out about ischemia, angina pectoris, ECG, etc. The causes of ischemia, its effect, the criterion of angina pectoris and its relation with the features in ECG signals are also described elaborately.

2.2 Mechanical and Electrical Properties of Heart

The heart is a four chambered pump. The top two chambers are called *Atria*, the bottom two are called *Ventricles*. They are separated from top to bottom by valves; the right and left sides are separated by a septum as given in Figure 2.1.

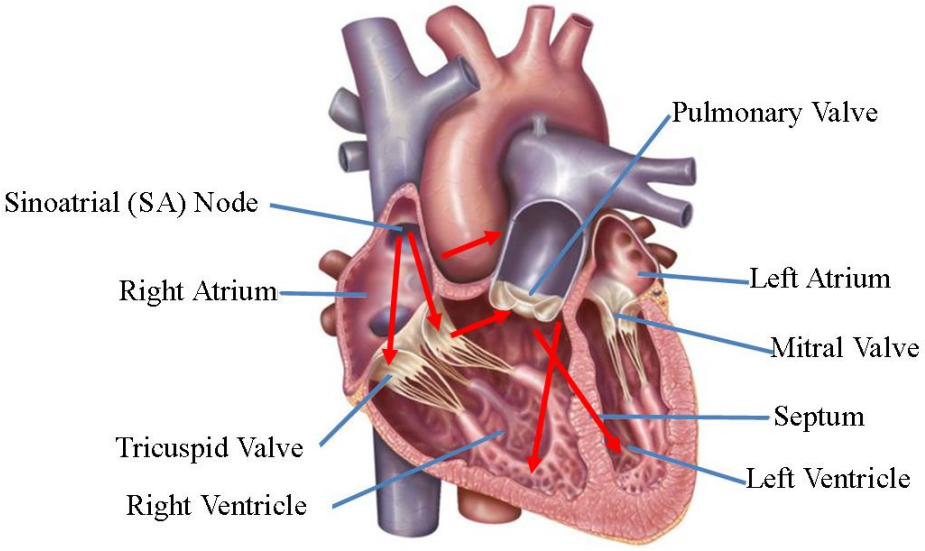


Figure 2.1 Heart anatomies with significant areas [12].

The heart is a muscle and functions primarily as a double-sided pump. The left side of the heart pumps oxygen rich blood to all parts of the body, while the right side of the heart pumps blood back to the lungs to pick up more oxygen. For this pump to operate, it needs a source of power or energy, in this case electricity.

The heart consists of four chambers: two upper chambers called the left and the right atria and two lower chambers known as the right and left ventricles. Between these upper and lower chambers are valves which open and close to direct the flow of blood. The left ventricle performs the most work and is the strongest of the four chambers. It ejects blood into the aorta: the main pipeline which comes out of the heart supplying oxygenated blood to the entire body [13].

During a normal heartbeat, an electrical impulse originates in the right atrium where the main pacemaker of the heart is located. This natural pacemaker is called the sinoatrial node (SA node). The impulse then travels to the left atrium and down the interatrial septum to the atrioventricular node (AV node). This is the secondary pacemaker to the heart.

The AV node slows down these impulses while they continue travelling down a common pathway branching off into the right and left bundle-branches and eventually to the ventricles. This cycle is known as normal sinus rhythm (NSR), which describes a well synchronized pumping action between the upper and the lower chambers producing the familiar (lub-dub) heart sounds [14].

2.3 Angina Pectoris

2.3.1 Ischemia

The heart muscle is a special type of muscle which has property of both voluntary and involuntary muscles. It contracts regularly and continuously to pump and circulate blood to the body and the lungs. The pumping action is caused by a flow of electricity through the heart which continuously repeats with a cyclic rhythm. If this electrical activity is disrupted due to any kind of disturbance, it affects in the rhythm of heart which is called arrhythmia. Arrhythmia can affect the ability of heart to pump properly. Therefore, an arrhythmia is an irregular heartbeat or loss of rhythm of the heart. During an arrhythmia the heartbeat may change regularity such as beat too fast, too slow or contract too early [15].

Ischemia or Myocardial ischemia is a very common disease for cardiac patient. Generally it happens due to the lack of sufficient blood flow in specific area of the heart named by contractile cells and this effect 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 [16]. It is considered that this may be the first instance where the subject begins to experience effects of the suboptimal operation of the heat due to insufficient blood supply.

Myocardial ischemia, also called cardiac ischemia, can damage your heart muscle, reducing its ability to pump efficiently. A sudden, severe blockage of a coronary artery can lead to a heart attack. Myocardial ischemia might also cause serious abnormal heart rhythms [17]. In

Figure 2.2, a graphical representation is shown to clarify how the blood flow is blocked which causes insufficient oxygen flow.

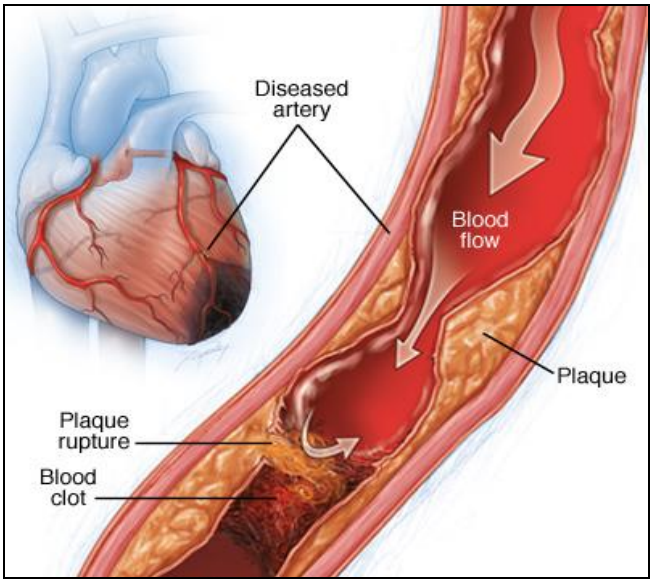


Figure 2.2: A pictorial representation of the blockage against blood flow that causes myocardial ischemia [8].

2.3.2 Angina Pectoris due to Ischemia

Angina pectoris, commonly known as angina, is usually severe chest pain or discomfort due to coronary heart disease. It occurs when the heart muscle becomes unable to get as much blood as it actually needs for normal functioning [18]. This usually happens because one or more of the heart's arteries become narrowed or blocked (as given in Figure 2.2). This phenomenon is also called ischemia. The symptom of angina often occurs when the heart muscle needs more blood than it is getting. During the times of physical activities or strong emotions, generally heart rates are increased while demand of oxygen by the heart muscle is increased as well. Severely narrowed arteries usually fail to allow enough blood to reach the heart and due to this consequence a patient feel uncomfortable pressure, fullness, squeezing or pain in the center of the chest. It may also feel the discomfort in neck, jaw, shoulder, back or arm of a patient.

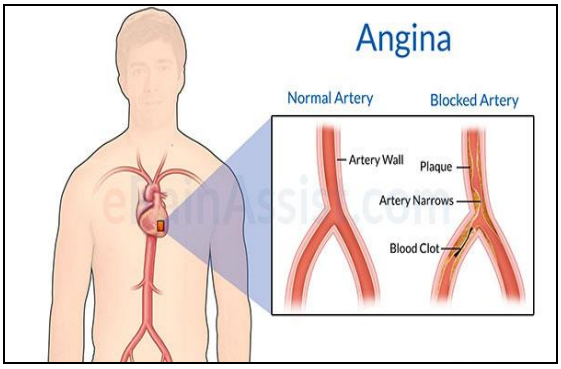


Figure 2.3: Normal and angina affected artery condition of heart [19].

2.3.3 Types of Angina

There are several different kinds of angina those are explained here. Generally, there are five different kinds of angina have been identified [20], with the two most common being stable angina and unstable angina.

Stable Angina: Stable angina occurs when the heart has to work harder than normal, during exercise, for example. It has a regular pattern, and if you already know that you have stable angina, you will be able to predict the pattern. Once you stop exercising, or take medication (usually nitroglycerin) the pain goes away, usually within a few minutes.

Unstable Angina: It is more serious, and may be a sign that a heart attack could happen soon. There is no predictable pattern to this kind of angina; it can just as easily occur during exercise as it can while you are resting. It should always be treated as an emergency. People with unstable angina are at increased risk for heart attacks, cardiac arrest, or severe cardiac arrhythmias (irregular heartbeat or abnormal heart rhythm).

Less common kinds of angina: It includes variant angina, microvascular angina, and atypical angina. *Variant angina* is also known as Prinzmetal's angina. It often occurs while someone is resting (usually between midnight and 8:00 in the morning), and it has no predictable pattern—that is, it is not brought on by exercise or emotion. This kind of angina may cause severe pain, and is usually the result of a spasm in a coronary artery. Most people who have variant angina have severe atherosclerosis (hardening of the arteries), and the spasm is most likely to occur near a buildup of fatty plaque in an artery. *Microvascular angina*—sometimes referred to as Syndrome X—occurs when tiny vessels in the heart become narrow and stop functioning properly, even if the bigger arteries are not blocked by plaque. Usually it is treated with common angina medications. *Atypical angina* often doesn't cause pain, but you may feel a vague discomfort in your chest, experience shortness of

breath, feel tired or nauseous, have indigestion, or pain in your back or neck. Women are more likely than men to have feelings of vague chest discomfort [21].

2.3.4 The Factors of Risk for Angina

One of the main causes of angina is **coronary artery disease (CAD)**. This describes a disease in which build-ups of fatty deposits block the flow of blood through the arteries. If we are exercising, cells in the heart (myocardium) may require additional oxygen (and more blood), but a blockage in the artery means it is not able to handle this extra demand. So what happens? The message about this lack of oxygen and blood is translated by our brains as pain, but if you rest or take medication, the pain will go away.

An inadequate amount of oxygen supplied to body tissue is called ischemia, and we therefore use the term myocardial ischemia to mean that there is not enough oxygen being supplied to our heart muscle. Angina doesn't usually starve our cells of oxygen completely, so they don't die.

Angina may also be caused by coronary artery spasm. This happens if any of the blood vessels that supply our heart muscle contract strongly. Such a contraction can cause a decrease or complete stop of the flow of blood to the heart, and this can lead to a heart attack. Coronary artery spasm can also be caused by the use of drugs like cocaine.

Risk factors for angina are similar to those for other heart disease, and include:

- High blood pressure.
- Diabetes.
- Unhealthy cholesterol levels.
- Smoking.
- Lack of exercise.
- Obesity
- Too much salt in your diet.
- Excessive use of alcohol.
- Family history of CAD or stroke.
- Being male.

- Being a postmenopausal woman.
- Age - the risk increases for men over the age of 45 and for women over the age of 55

2.3.5 Symptoms of Angina: The symptoms of angina are different for different people, but regardless, they are usually experienced after heavy exercise or because of emotional stress. Learn to recognize and pay attention to the following symptoms:

- Pain that begins in the middle of your chest and then spreads to your left arm, back, neck or jaw; usually this is not a sharp pain, but a dull one.
- A feeling of pressure, tightness or squeezing in your chest or arms.
- A feeling of persistent indigestion that is moderate or severe.
- Numbness, or a lack of feeling in your arms, shoulders or wrists

The symptoms vary according to the type of angina you have. If, for example, you have **stable angina**, the pain or discomfort:

- Happens when your heart has to work harder, during exercise for example.
- Is no surprise to you, and feels the same each time it happens.
- Usually lasts less than 5 minutes, and stops if you rest or take medication.
- Might feel like indigestion.

Unstable angina is different. The pain or discomfort:

- Often happens when you are sleeping or resting.
- Takes you by surprise.
- Might last as long as 30 minutes and might become progressively worse.
- Cannot be relieved with rest or medication.
- Might be a sign of a heart attack that will happen soon.
- Unstable angina tends to happen more often in older adults.

2.4 Normal ECG waves and its features

Atrial and ventricular depolarization and repolarization are represented on the ECG as a series of waves: the P wave followed by the QRS complex and the T wave**.**

2.4.1 P Wave: The first deflection is the P wave associated with right and left atrial depolarization. Wave of atrial repolarization is invisible because of low amplitude. Normal P wave is no more than 2.5 mm (two-and-a half1-mm-divisions) tall and less than 120 ms (three 1-mm-divisions) in width in any lead. In sinus rhythm when the SA node is the pacemaker, the mean direction of atrial depolarization (the P wave axis) points downward and to the left, in the general direction of lead II within a coordinate between 15^0 and 75^0 and away from lead aVR. On this count the P wave is always positive in lead II and always negative in lead aVR during sinus rhythm. Conversely, a P wave that is positive in lead II and negative in lead aVR indicates normal P wave axis and sinus rhythm.

2.4.2 QRS Complex: The QRS complex is the largest voltage deflection of approximately 10– 20 mV but may vary in size depending on age, and gender. The voltage amplitude of QRS complex may also give information about the cardiac disease [22]. Duration of the QRS complex indicates the time for the ventricles to depolarize and may give information about conduction problems in the ventricles such as bundle branch block.

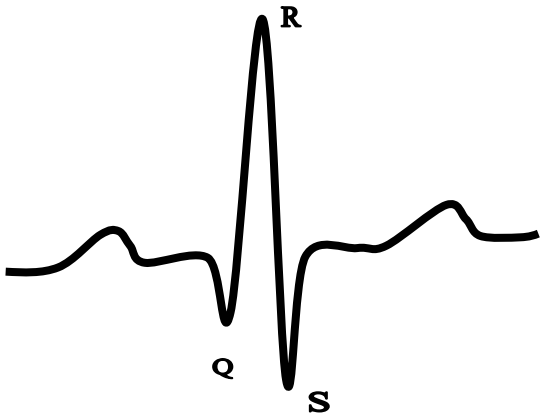


Figure 2.4: A QRS complex with QRS deflections.

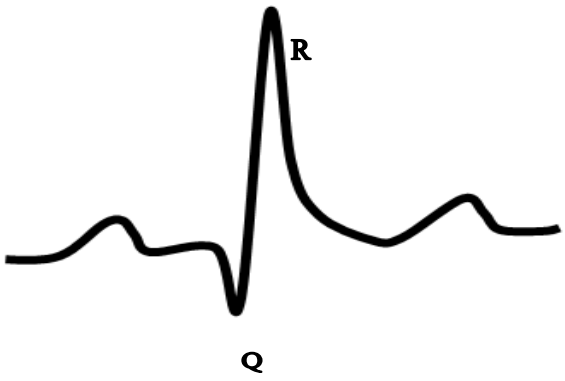


Figure 2.5: A QRS complex with QR deflections.

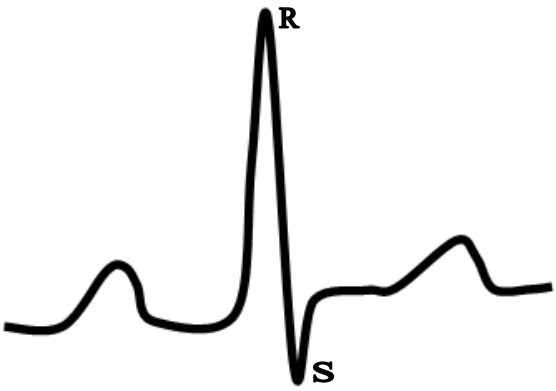


Figure 2.6: A QRS complex with RS deflections.

2.4.3 T Wave: The T wave represents the current of rapid phase 3 ventricular repolarization (see diagram above). The polarity of this wave normally follows that of the main QRS deflection in any lead. The ventricles are electrically unstable during that period of repolarization extending from the peak of the T wave to its initial downslope. A stimulus (e.g. a run away heart beat called a premature beat) falling on this vulnerable period has the potential to precipitate ventricular fibrillation: the so call R-on-T phenomenon.

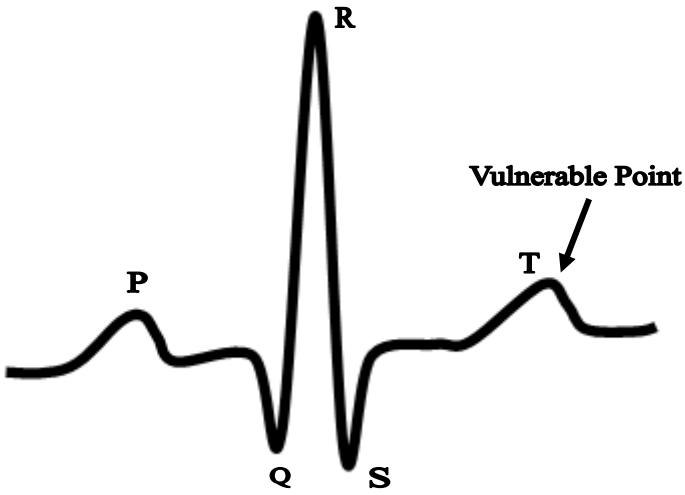


Figure 2.7: Graphical Presentation of a Normal T Wave.

2.4.4 ST Segment: Following the QRS complex is the ST segment, extending from where the QRS ends (irrespective of what the last wave in the complex is) to where the T wave begins. The junction between the end of the QRS and the beginning of the ST segment is called the J point. ST segment reflects the current flow associated with phase 2 of ventricular

repolarization. Since there is no current flow during this plateau phase of repolarization, the ST segment is normally isoelectric with the baseline. Therefore in the absence of any cardiac pathology, the end of depolarization and the beginning of repolarization are normally isoelectric; this region is called the ST segment. On the ECG signal, the ST segment is defined as the region between the ends of the S-wave, also called the J-point, and the beginning of the T-wave. ST Segment is shown in Figure 2.7.

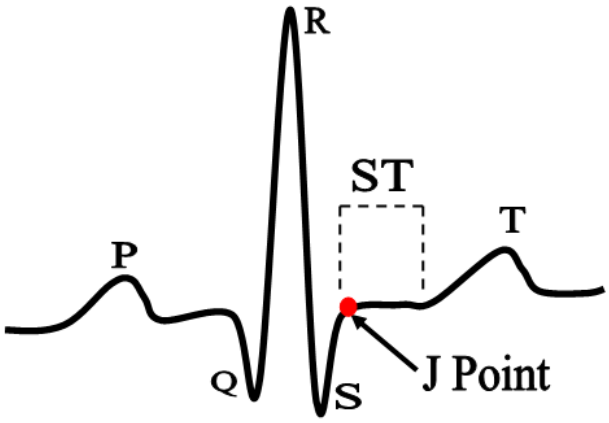


Figure 2.8: Graphical Representation of Normal ST Segment Indicating J point.

The current standard of determining the ST segment measurement is by measuring the voltage difference between the value at a point 60 -80 milliseconds after the J-point and the isoelectric baseline. The isoelectric baseline is either between the P- and Q-waves (the P-R interval) or in front of the P-wave (the T-P interval) which shown in Figure 2.8.

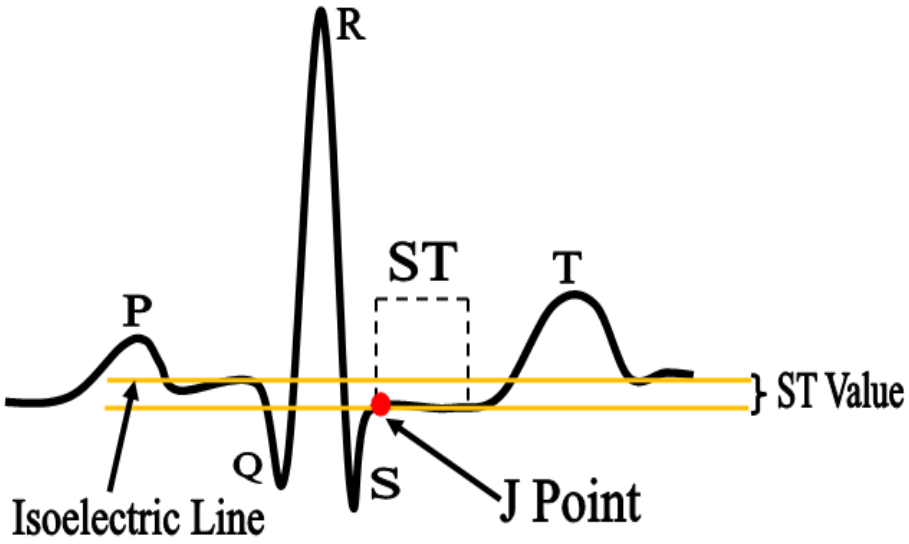
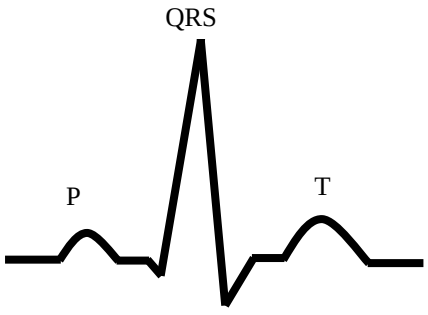


Figure 2.9: ST Segment Measurement.

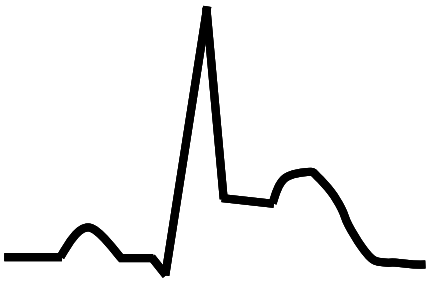
2.5 ECG and Its Characteristics during Angina

The pain of angina generally begins beneath the sternum as a vague pain. It may proceed to a severe, crushing, or intense pain that may radiate to the left shoulder, down the arm, to the back, throat, or even the jaws and teeth. Typical angina is often associated with atherosclerosis; with the accompanying plaque formation in the coronary vessel, occludes blood flow to the myocardium. ECG changes associated with typical angina include ST depression. Two types of effects are found in ECG signals and those are ST elevation and ST depression which is shown in Figure 2.9. In typical angina pectoris, ST segment is depressed 1 to 2-mm which is visualized in V_5 and V_6 lead. But this change is transient, after two hours ST segment it come to normal. In chronic angina pectoris ST segment is depressed as well as T wave is inverted.

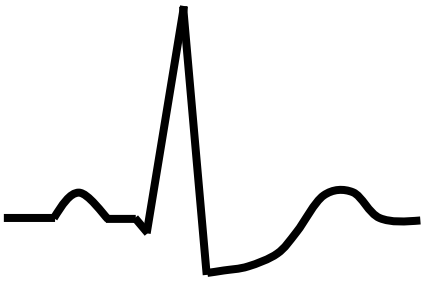
The main characteristic of ischemia in the cellular level is the depolarization of the cellular resting membrane potential. As large areas of the heart muscle become ischemic, its relaxation and contraction patterns are affected, which cause variations in the ST level and T-wave in ECG due to the development 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 heat to arrhythmias.



(a) Normal ECG



(b) A Typical Angina: ST Elevation



(c) A Typical Angina: ST Depression

Figure 2.10: A typical angina pectoris characteristics

The effect of angina is strongly connected with the behavior of S-T segment of the ECG signal [23]. To prepare a demo ischemia in heart, exercise ECG is considered for diagnosis of angina because this process is more sensitive and specific than the resting ECG in detecting myocardial ischemia [24]. The ECG of the affected patients change associated with myocardial ischemia includes horizontal or down-sloping ST-segment either in depression or elevation. It is observed that this effect on ST segment occurs after 60-80ms of the end of the QRS complex. Especially when the behavior of ST segments is accompanied with chest pain it is suggested to angina. Angina pectoris is occurred at a low workload during the early stages of exercise and it persists for more than 3 minutes after exercise [25]. Increasing the threshold of a positive test to $\geq$ 2mm (0.2mV) ST-depression, will increase specificity at the expense of sensitivity.

Table 2.1: Characteristics of Normal ECG waveform

Peak Wave	Amplitude (mV)	Peak to Peak Interval	Parameter Duration in second
P	0.25	RR	0.12-.20
R	1.60	QRS	0.09
Q	25% of R wave	QT	0.31-0.44
T	0.1-0.5	ST	0.05-0.15

2.6 Chapter Summary

In this chapter, the main causes of Ischemia and corresponding angina pectoris are discussed. In addition, the effect of angina pectoris on ECG signal pattern is also discussed and the dissimilarity with the normal ECG signal pattern is also explained in this chapter. Eventually, this chapter indicates the technical way to find the angina pectoris from ECG signal pattern.

CHAPTER 3: Methodology

3.1 Introduction

Since the goal of this paper is to identify the angina pectoris from ECG signal, an algorithm is developed that is able to meet the challenge by a number of signal processing steps. This algorithm is able to detect the normal and abnormal peaks of ECG signal based on the characteristics of ST segment. From the signal loading to the final step to decide the presence of angina is presented by the block diagram given in Figure 3.1. The major steps given in this block diagram are discussed gradually in the following.

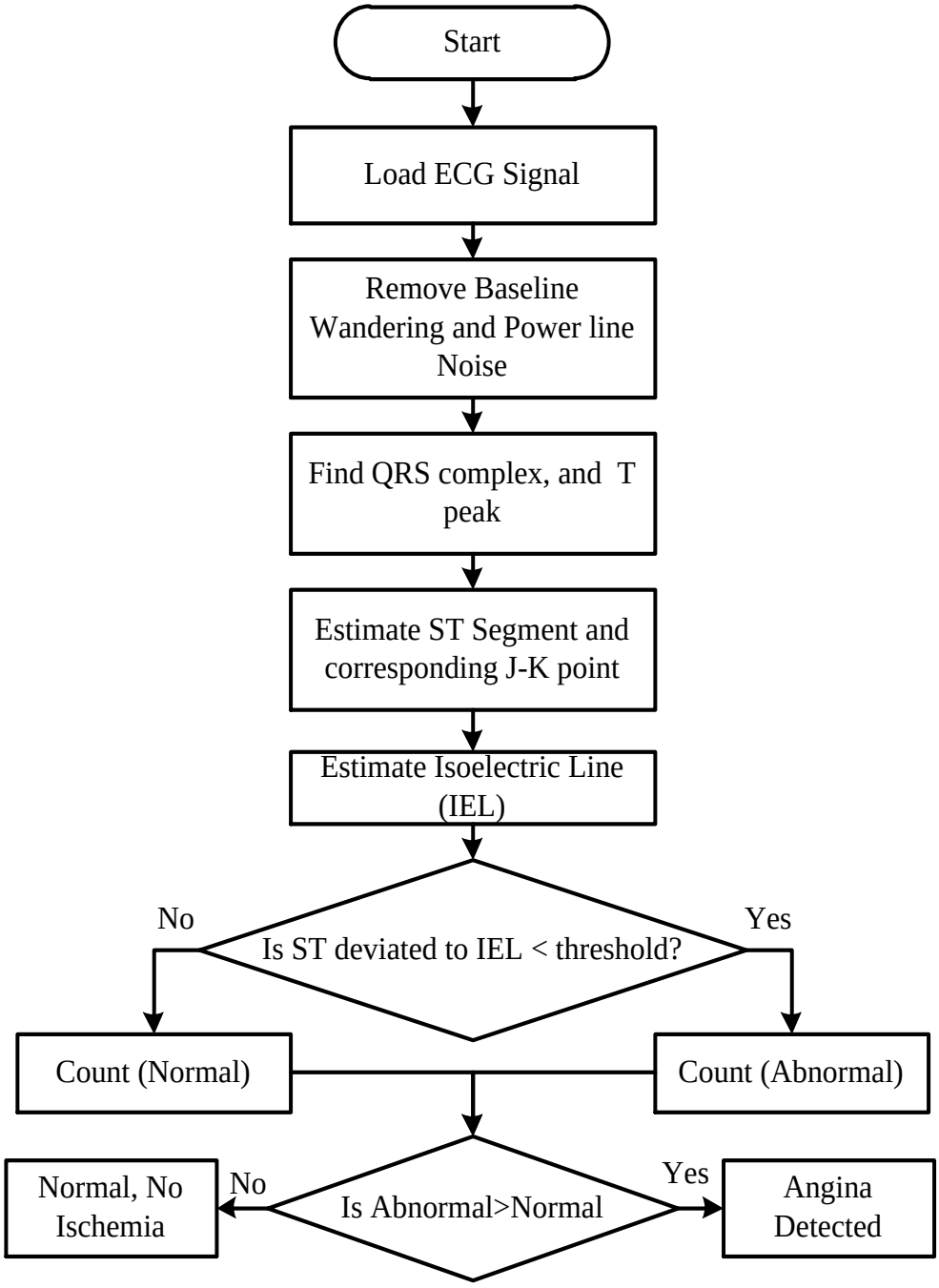


Figure 3.1: Block Diagram of Computer based Angina Pectoris Detecting Algorithm from ECG Signal

3.2 Baseline Wandering Removal

After signal loading first preprocessing step is to remove the baseline wander from the raw ECG signal. Baseline wander is removed from the ECG signal by BWPF (baseline wander path finding) algorithm described in [26] which is designed by the polynomial fitting technique with multiple segmentation of the signal.

By this methodology, total signal cannot be considered for polynomial fitting. This is because with a very high degree of polynomial will also be unable to trace the path of wandering. Considering this fact, after loading the full length ECG signal, it is divided into several segments which help to divide the wandered path into several limited ordered wandered ECG signal. The procedure to implement BWPF algorithm is presented by block diagram given in Figure 3.2.

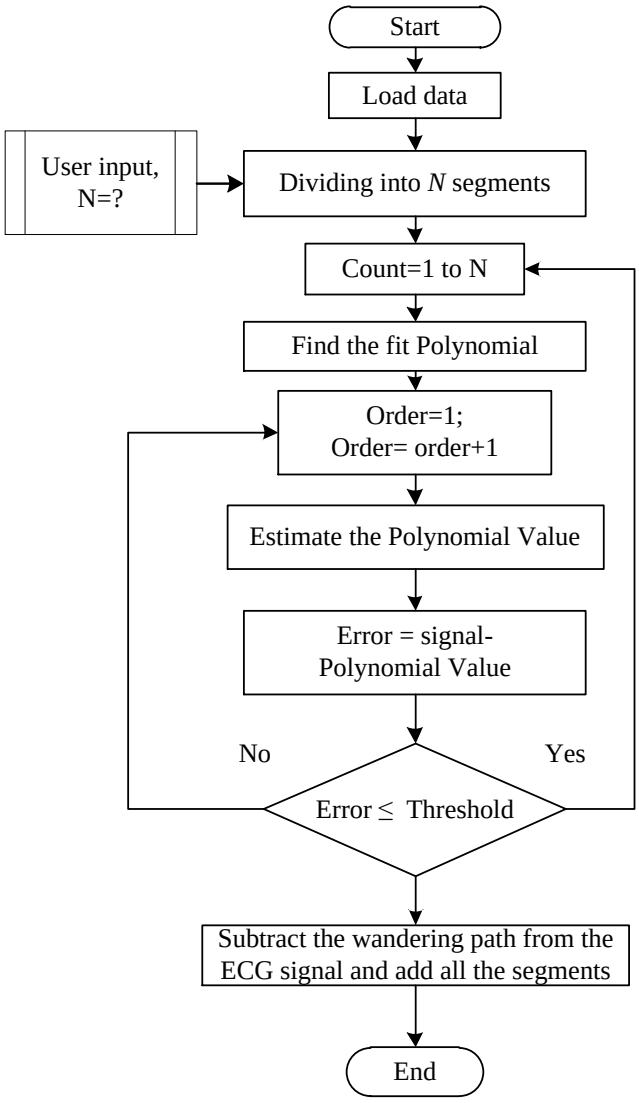


Figure 3.2: Block diagram of BWPF algorithm

In this algorithm, segmentation number is taken as user or operator input based on the wandering path presented in ECG signal. Polynomial fitting order is self-assessed in our proposed methodology based on the threshold value of fitting. The algorithm starts from order 1 to fit the ECG wandering path and compute its fitting error to compare the standard value given as threshold. If the error is greater than the threshold value the process is repeated with the order=previous_order+1 and will continue the process to achieve the error value less than or equal to the threshold value. After fitting all the segments by different order and different values, the wandering paths are subtracted from the segmented signals and add together to represent the previous signal as wander free. After that the signal can be simply filtered to prepare it for the further processing like heart rate calculation, peaks identification, ischemia detection, angina pectoris identification, etc.

3.3 Noise Removal from the ECG signal

The aforementioned algorithm finds the wandering path and finally this path is subtracted from the raw ECG signal which gives baseline corrected signal. After that the noise presented in ECG signal can be removed by the Gaussian weighted moving average filter. In this type of moving average filter the center value of the window is weighted generally two or three times than the other values for convolution. Since moving average filter, using as FIR criteria, has a property of low pass filter. Besides there are several noises hiving the frequency level is below the cutoff frequency and nearer to zero those can be incorporated due to low pass filter. Sometimes, the QRS complex of ECG signal becomes broad and distorted for the activation pulse originating in the ventricle as well as not going the actual conduction path. Frequency domain analysis of Fourier Transform can be applied to discriminate the high-frequency and low-frequency ranges of ventricular rhythm, atrial rhythm, parasympathetic and sympathetic activity signals. For example, spectral analysis is the linear transform used to diagnose ventricular tachyarrhythmia. Power spectrum of individual QRS complex is found significant differences in the 0–20 Hz frequencies. The spectrum in VT has maximum amplitude at 4 Hz [27]. Spectral analysis is also used in case of analyzing the heart rate variability (HRV) signals. Power spectra in the 0.15–0.5 Hz ranges reflect respiratory sinus arrhythmias and cardiac vagal activity. On the other hand, baro-receptor control is mediated by vagal and sympathetic systems in the 0.04–0.15 Hz ranges. In addition with that very low-frequency (~0.04 Hz) is related to thermoregulatory, vascular mechanisms and rennin-angio tension systems [28-29].

According to the previous discussion we can conclude that if we use low pass filter like Gaussian window moving average filter, we can remove high frequency noises from ECG signal normally. Nonetheless, if we clear out the all noises except ECG signal we should use bandpass IIR (infinite impulse response) filter. In that case our proposal to set the band for ECG signal filtering should be 0.5Hz-45Hz. It will remove all physiological and power line noises. Therefore, Gaussian windowed moving average filter has been discussed briefly.

Gaussian windowed moving average filter: In electronics and signal processing, a Gaussian filter is a filter whose impulse response is a Gaussian function (or an approximation to it). Gaussian filters have the properties of having no overshoot to a step function input while minimizing the rise and fall time. This behavior is closely connected to the fact that the Gaussian filter has the minimum possible group delay. It is considered that the ideal time domain filter, just as the sinc is the ideal frequency domain filter [30]. These properties are important in areas such as oscilloscopes [31] and digital telecommunication systems [32].

Since signal exhibits one-dimensional property, the one-dimensional Gaussian filter has an impulse response given by,

$$g(x) = \sqrt{\frac{a}{\pi}} e^{-a.x^2} \tag{3.1}$$

Here, *a* is a constant and x is the data vector. On the other hand, the frequency response from the previous relationship given by eqn. (3.1) we can estimate from the Fourier transform and which can be equated as given by the following relationship,

$$g(f) = e^{-\left(\frac{\pi.^2 f^2}{a}\right)} \tag{3.2}$$

Here, *f* is the ordinary frequency. These equations can also be expressed with the standard deviation as parameter in both time and frequency domains, and the relationships are presented by the following two eqn. (3.3) and (3.4), respectively [33-35],

$$g(x) = \frac{1}{\sqrt{2\pi}.\sigma} .e^{-\left(\frac{x^2}{2\sigma^2}\right)} \tag{3.3}$$

$$\hat{g}(f) = e^{-\left(\frac{f^2}{2\sigma^2}\right)} \tag{3.4}$$

By writing *a* as a function of σ with the two equations for $g(x)$ and as a function of σ_f with the two equations for $\hat{g}(f)$ it can be shown that the product of the standard deviation and the standard deviation in the frequency domain is given by,

$$\sigma.\sigma_f = \frac{1}{2\pi} \tag{3.5}$$

Where, the standard deviations are expressed in their physical units, e.g. in the case of time and frequency in seconds and Hertz.

It means the before and after of the ECG signal we have added 100 vectors as zero. The window length is considered as 15. The MATLAB command *gausswin*() returns us the convolutional parameters of 15 window size and the output filtered signal is achieved by the multiplication with the gaussian window values and corresponding addition (can be called as convolution) obeying the principle of moving average filtering.

3.4 QRS Complex Detection

The QRS complex duration is one of the major parameters in the field of the ECG signal analysis. QRS complex are the middle part between P and T wave. 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 intra-ventricular conduction delay when the QRS interval is between 0.1 to 0.12 seconds. For QRS complex detection we used the FS2 algorithm and amplitude threshold in this work.

The FS2 algorithm is designed based on the first and second derivative of ECG signal which was developed by Balda [37] in 1977, and further modified by Ahlstrom and Tompkins [38] in 1983, for high speed R-peak detection of recorded ECG signals. The first and. second derivatives act as high pass filters which attenuates the low frequencies. To implement the algorithm the absolute value is taken from the first derivative of the original signal as given in (3.9) and (3.10).

$$Y_0(n) = \left| ECG(n+1) - ECG(n-1) \right| \tag{3.9}$$

$$Y_1(n) = \left| ECG(n+2) - 2 * ECG(n) + ECG(n-2) \right| \tag{3.10}$$

The first derivative is then smoothed by a 4-point moving average low-pass filter as given in (3.11) and then added to the second derivative as (3.12). This reduces the P and T wave deflections. Since the P and T wave deflections are almost removed, the only peak found is QRS which gives us the location span of QRS peak. This result is implemented to the filtered ECG signal to find the QRS complex.

$$Y_1(n) = [Y_0(n-1) + 2 * Y_0(n) + Y_0(n+1)] / 4 \tag{3.11}$$

$$Y_2(n) = [Y_1(n) + Y_2(n)] \tag{3.12}$$

Finally, threshold is determined to find the R peak location from the signal. Generally, threshold = 0.8 * max(Y3(n)). A QRS candidate is found when the sum exceeds the primary threshold, QRS(n) = Y3(n) > primary threshold.

3.5 S -T Segment Estimation

S wave is the last wave in QRS complex. Since the QRS complex is already detected by the previous algorithm the S wave can be found through the minimum value in the range R_{loc}+5 to R_{loc}+50 [39]. On the other hand, T wave can be found between the range R_{loc}+25 to R_{loc}+100 [40]. The ST segment is the most important feature of the ECG for investigating angina pectoris. The ST interval is measured from the J point (the minimum point of S wave) to the end of the T wave. Basically, the highest point of T wave is also known as K point. The elevation and depression of ST segment together with the T-wave changes indicate the zone of ischemia around the applied lead. First we identified the J point and T- onset. Then average amplitude between J point and T-onset is calculated.

3.6 Detection of Isoelectric Level and Comparison with ST Segment for Angina Detection

A reference level is necessary to measure the elevation or depression of ST segment. The Isoelectric line (IEL), which is the flat parts of the ECG can be used as this reference level. The IEL usually place between the T and P waves or between the P wave and the QRS

complex. The IEL is found from the flat portion of ECG characteristics points J and K. Then we compare the ST segment level with the isoelectric line level. If this segment is considerably underneath the isoelectric line then ST segment depression occurs which indicate that part of the patient`s myocardium is not receiving sufficient oxygen and results the myocardial ischemia. If the ST segment is raised above the isoelectric line it indicates myocardial infarction.

More quantitatively, when ST level is greater than 0.08 mv underneath the isoelectric line and has slope of more than 65 degree with respect to the perpendicular axis of ECG, it is considered as ST depression [41]. On the contrary, ischemic is considered if ST segment is raised above the isoelectric line more than 0.08mv.

The algorithm is simulated in MATLAB environment using normal and affected patient's ECG signal from MIT arrhythmia database [42] to assess its effectiveness. The ECG signals named by ecg100_1, ecg100_2, ecg105, ecg109, ecg111, ecg112, ecg113, ecg114, ecg115, and ecg119 in MIT-Arrhythmia database are tested. For example, the average isoelectric line and ST segment level for ecg100_2 are found as: st_avg=-0.4951 mv and iso_avg = -0.4060. The resultant subtracted value is -0.0891 mv which shows that ST segment is deviated below the isoelectric line and hence it is considered as ST depression or negative ST deviation.

3.7 k-Nearest Neighbor Classification

Since the previously explained method depends on only one feature to distinguish the normal and abnormal ECG pattern which may be often proved unacceptable. It will be more accurate approach if we consider a number of significant features of the ST segment like slope, standard deviation, energy, skewness, etc. For multiple comparisons the machine learning approach is more suitable and acceptable approach. In this sense, kNN based method is better than the other method like linear discrimination analysis (LDA) and Bayesian algorithm (BA). In this project, we have used kNN based predictive model to find the total normal and abnormal ST segment in each ECG signal.

Nearest neighbor is a nonparametric estimation method that implements a refinement where the feature environment is high resolution in regions with dense training and low resolution in variance. The method works based on the following steps.

- Suppose, Z(z) $\subset \mathbb{R}^N$ is a hypersphere of volume, ν and center, z. Let us, consider that the training set S_k consists of N_k number of samples. Therefore, according to binomial distribution, the probability of including precisely n samples within the hypersphere, Z(z) can be equated by the following expectation.

$$E[n] = N_k \int_{y \in Z(z)} p(y \mid w_k) \approx N_k \nu \; p(z \mid w_k) \tag{3.13}$$

Here, w_k represent the number of class.

- The radius, z of the sphere *Z* is selected in way that *Z* contains exactly κ samples. In this sense, the volume becomes the function of *z* and it can be presented as $\nu(z)$. So, the estimation of density based on the number of κ can be calculated as,

$$\hat{p}(z \mid w_k) = \frac{\kappa}{N_k \nu(z)} \tag{3.14}$$

- The parameter, κ can control the stability between the variance and bias. To classify any vector, $\hat{z}$ the radius of the sphere is selected such a way that the sphere contains exactly κ samples occupied from Sk. These samples are termed as the κ-nearest neighbor. Let κ_k indicates the number of samples originated with the class w_k. The conditional density is estimated as the following relationship given in (3.15).

$$\hat{p}(z \mid w_k) \approx \frac{\kappa_k}{N_k \nu(z)} \tag{3.15}$$

The following distances can be chosen to find the expected nearest neighbor:

1. Minkowski Distance: The Minkowski distance of order *p* between two real points $X=(x_1, x_2,\ldots, x_n)$ and $Y= (y_1, y_2,\ldots, y_n)$ is defined as,

$$d_{MK}(X,Y) = \sum_{i=i}^{n} \left(\left| x_i - y_i \right|^p \right)^{1/p} \tag{3.16}$$

For $p \geq 1$, the Minkowski distance is a metric as a result of the Minkowski inequality. When $p \geq 1$, the distance between (0,0) and (1,1) is $2^{1/p} \geq 2$, but the point (0,1) is at a distance 1 from both of these points. Since this violates the triangle inequality, for $p \geq 1$it is

not a metric. Minkowski distance is typically used with *p* being 1 or 2, which correspond to the Manhattan distance and the Euclidean distance, respectively.

2. Manhattan Distance: The Manhattan Distance or taxicab geometry is a form of geometry in which the usual distance function or metric of Euclidean geometry is replaced by a new metric in which the distance between two points is the sum of the absolute differences of their Cartesian coordinates. The taxicab distance, d_1, between two vectors *p*, *q* in an *n*-dimensional real vector space with fixed Cartesian coordinate system, is the sum of the lengths of the projections of the line segment between the points onto the coordinate axes. More formally,

$$d_{MD}(X,Y) = \|X - Y\|_1 = \sum_{i=i}^{n} |X_i - Y_i| \tag{3.17}$$

3. Euclidean Distance: In mathematics, the Euclidean distance or Euclidean metric is the "ordinary" straight-line distance between two points in Euclidean space. With this distance, Euclidean space becomes a metric space. The associated norm is called the Euclidean norm. Older literature refers to the metric as Pythagorean metric. A generalized term for the Euclidean norm is the L^2 norm or L^2 distance. The Euclidean distance between points X and Y is the length of the line segment connecting them ($\overline{XY}$). In Cartesian coordinates, the Euclidean distance is measures as,

$$d_{ED}(X,Y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + ... + (x_n - y_n)^2} = \sqrt{\sum_{i=1}^{n} (x_1 - y_1)^2} \tag{3.18}$$

The position of a point in a Euclidean *n*-space is a Euclidean vector. The following figure can create a clear concept between the distance of Euclidean distance and Manhattan distance.

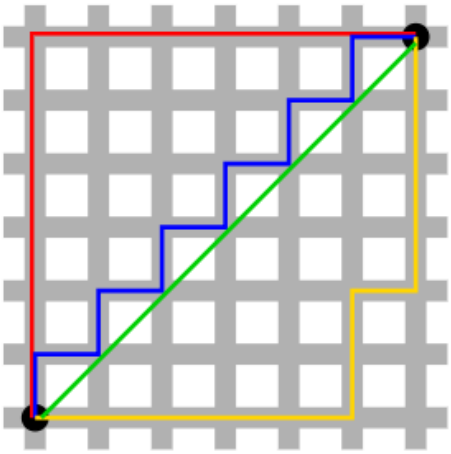


Figure 3.3: Manhattan distance (Red), Euclidean Distance (Green). Both blue and yellow are also equivalent to Manhattan distances.

4. Chebyshev Distance: In mathematics, Chebyshev distance (or Tchebychev distance), maximum metric, or L_∞ metric is a metric defined on a vector space where the distance between two vectors is the greatest of their differences along any coordinate dimension. It is named after Pafnuty Chebyshev. The Chebyshev distance between two vectors or points X and Y, with standard coordinates x_i and y_i, respectively, is

$$d_{CV}(X,Y) = \max_i(|X_i - Y_i|) \tag{3.19}$$

Mathematically, the Chebyshev distance is a metric induced by the **supremum norm** or **uniform norm**. It is an example of an injective metric. From the Figure 3.5, we can understand the Chebyshev distance calculating procedure as a pictorial interface. We can see that the points where the distance is maximum, is considered to take it the actual distance through the procedure described by Chebyshev distance.

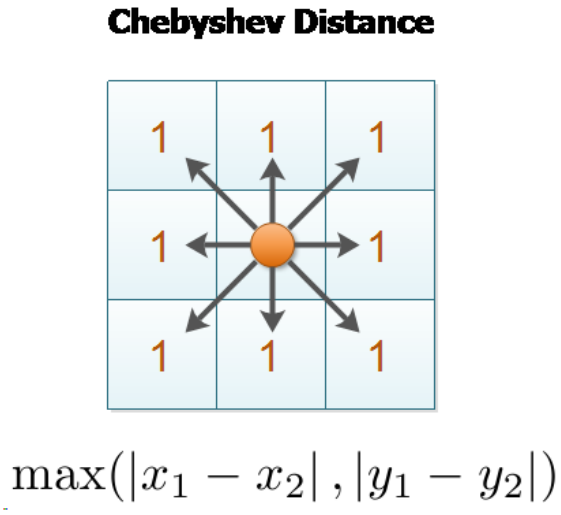


Figure 3.5: Pictorial illustration of Chebyshev distance calculating procedure

3.8 Performance Measurement Criteria

The performances of the classifiers were determined by the calculation of sensitivity, specificity, and total classification accuracy by the following relationships.

$$\text{Sensitivity (True positive rate)} = \frac{TP}{TP + FN} \tag{3.20}$$

$$\text{Specificity (False positive rate)} = \frac{TN}{TN + FP} \tag{3.21}$$

$$\text{Total classification accuracy} = \frac{TN + TP}{TN + FN + TP + FP} \tag{3.22}$$

Where,

Total number of correctly classified positive patterns = TP,

Total number of actual positive patterns = $TP+FN$

Total number of correctly classified negative patterns = TN

Total number of actual negative patterns = $TN + FP$

Total number of correctly classified patterns = $TN + TP$

Total number of applied patterns = $TN + FN + TP + FP$.

3.9 Chapter Summary

In this chapter the mathematical details for the governing methods of the project work has been discussed with proper graphical representations and technical details of the applicability of the methods. In the next chapter, all the results have been presented with discussion.

CHAPTER 4: Results and Discussions

4.1 Introduction

For the performance measurement, MIT-arrhythmia database (most standard ECG database for myocardial disease) is used in this work. The project is accomplished by designing an algorithm in MATLAB platform. The signal processing and analysis of ECG signal is done by the code written in MATLAB 2012b. In this algorithm, some predefined well known functions are used. On the other hand, a number of functions have been created as required to estimate different properties of ECG signal. Finally a complete algorithm is developed to check the angina existence in ECG signal. The performance of the proposed algorithm is measured by some metrics like accuracy, sensitivity, and specificity. The real condition and the results achieved by proposed work is also compared in this section.

4.2 The MIT-BH Arrhythmia Database

Academic and industry research groups have long studied irregularities of the heart cycle and identification of arrhythmias, and having access to databases of ECG recordings has been a useful tool for these activities. The MIT-BIH Arrhythmia Database, found on the PhysioNet web site, is a free-to-use database that has been available since 1980, and has been regularly used for the evaluation of arrhythmia detectors; as Moody [43] said, by having the availability of the databases, the general standard of commercial arrhythmia detectors has improved rapidly.

The database originated from the Arrhythmia Laboratory of the Beth Israel Hospital (BIH) for the intent of making them available to the research community. There are a total of 48 signals available and were taken from patients aged 23 to 89 years old.

The recordings were made using one of nine DEL Mar Avionics model 445 two channel reelto-reel Holter recorders, whilst the digitising used a Del Mar Avionics 660 playback unit. Each digital record lasts approximately 30 minutes and contains 650000 samples; the digitising rate was produced at 360 samples per second which accommodated a simple 60Hz notch filter implementation. The ECG lead or electrode placement varied with some patients, however in most cases they were recorded using the modified limb lead II (MLII).

Four of the 48 recording had pacemaker artifacts that were not accurately reproduced due to the pass band filter used during the analogue to digital conversion. These unwanted variation in signals have the ability to substantially affect the results obtained from peak detection algorithms. This has given researchers additional challenges to overcome when designing new algorithms

4.3 Preprocessing Results of the ECG Signal

According to the previous description provided in chapter 3, at first the raw ECG signal is loaded. After loading the ECG signal, baseline wandering was removed from the signal. It is already mentioned that the baseline wander removing method was followed by BWPF algorithm. By this algorithm, the baseline wander is sectioned by some suitable part of the total length of the signal. Then, from every part of the raw ECG signal, the baseline path is estimated by polynomial fitting. The polynomial fitted path is subtracted from the raw ECG signal. Eventually the raw baseline wandered signal turned into baseline wander removed signal or baseline wander free signal. The result of the BWPF algorithm on MIT-arrhythmia ECG signal is shown in Figure 4.1. From the figure, we came to know that the result removes the baseline wander from the raw ECG signal.

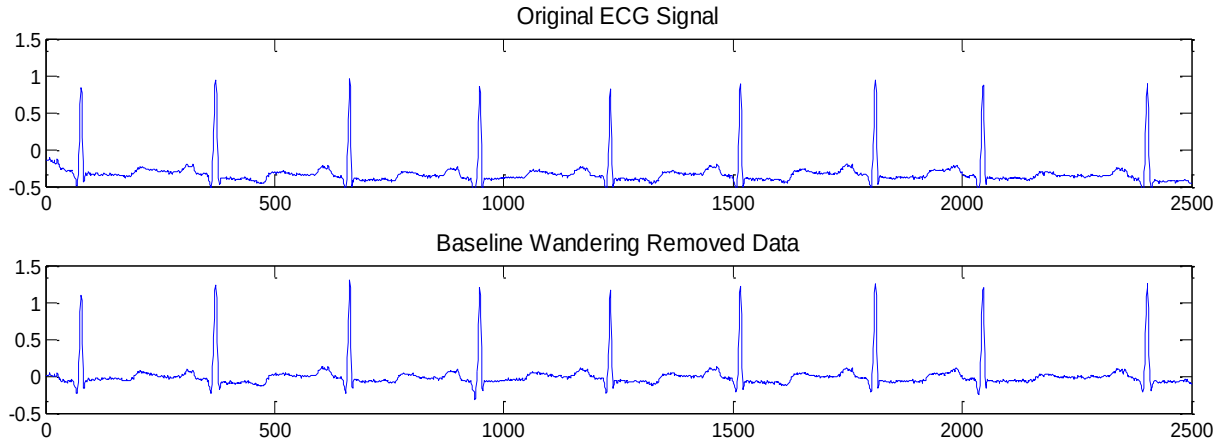


Figure 4.1: Baseline Wander Removal and Filtering Effect of ECG Signal

Noise removal from the ECG signal:

The preprocessing part of angina pectoris detection is very important. Besides baseline wander removal and noise cancellation different point of ECG signal like P peak, QRS complex, S-T Segment, J &K point identification cannot be possible appropriately. Without these properties estimation, no one cannot achieve computer based angina pectoris detection algorithm.

On this consequence, after baseline wander removal the physiological and power noises are removed from the signal. There are two types of noise cancellation choices in this case. One is lowpass filtering and another is bandpass filter. Since, baseline wander is removed by the advanced algorithm (BWPF), no need to use bandpass IIR filter. Therefore, on this condition

noises are removed by Gaussian window based moving average filer. It is well known that the moving average filter has significant property of low pass filtering. In this project, Gaussian window is used so that the R peak would not be decreased significantly by the effect of moving average filter. The baseline wander removed signal with noise and noise free signals are shown in Figure 4.2 where it is observed that the signal becomes quite noise free and smoothed.

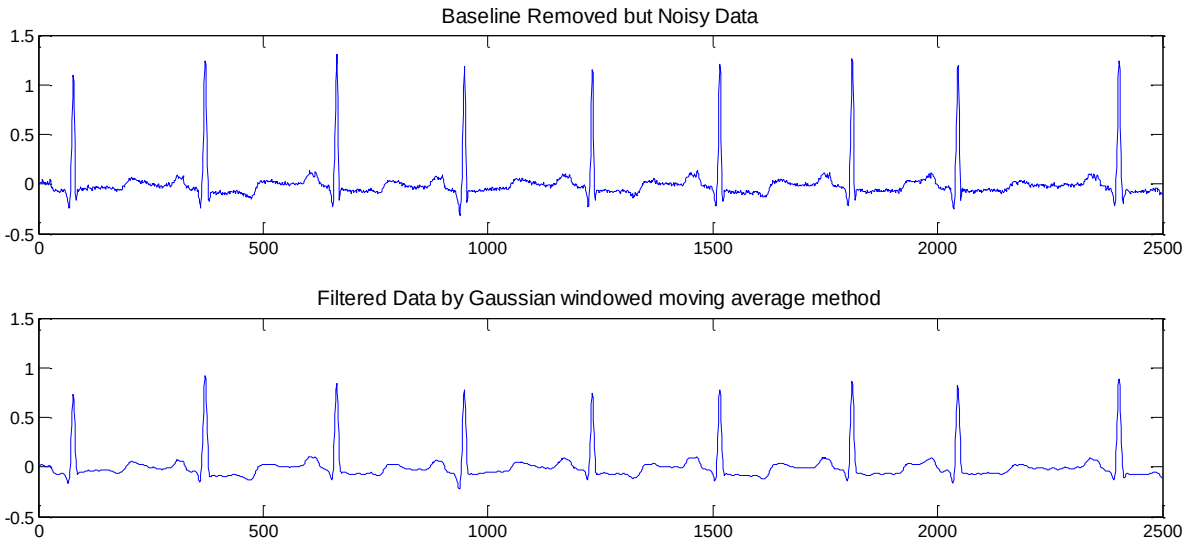


Figure 4.2: Noisy ECG Signal and Filtered ECG Signal

4.4 QRS Complex Detection

Since QRS complex detection is very important role for this project, most widely used and sophisticated method FS2 algorithm is used. FS1 algorithm can be used as well but FS2 is more accurate. In this algorithm, 1st and 2nd derivation of original signal is used obeying the rule described by the relationships by equation 3.9 to 3.12. For QRS complex detection amplitude threshold is also used. The proper concept can be achieved by the program code given in Chapter III.

According to the FS2 algorithm every steps from filtered ECG signal to reach the QRS complex are calculated and presented by the Figure 4.3. From the figure, we can observe that the 1st and 2nd derivative effect of the signal and the variation formed by the FS2 algorithm. By the application of FS2 algorithm on ECG signal all other peaks like P and T became flat and on that point depending on some threshold value, QRS complex is detected.

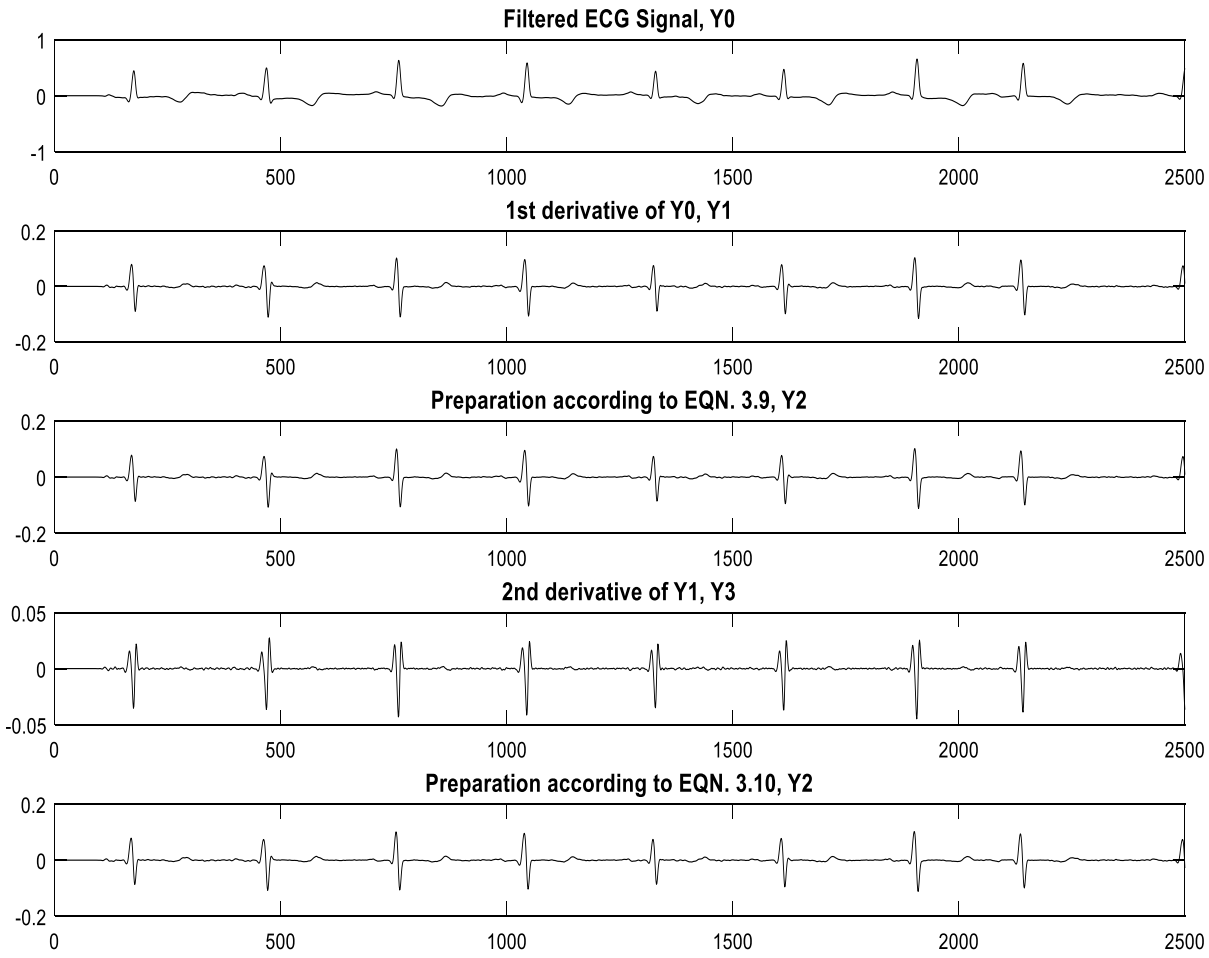


Figure 4.3: Effect of Every Steps of FS2 Algorithm on ECG Signal

Considering the threshold described in chapter 3, the Q, R, and S points are detected by our algorithm. The techniques are described by the code given in previous chapter. Figure 4.4 depicts the corresponding QRS points. In addition with that, the points are registered in original ECG signal given in Figure 4.5.

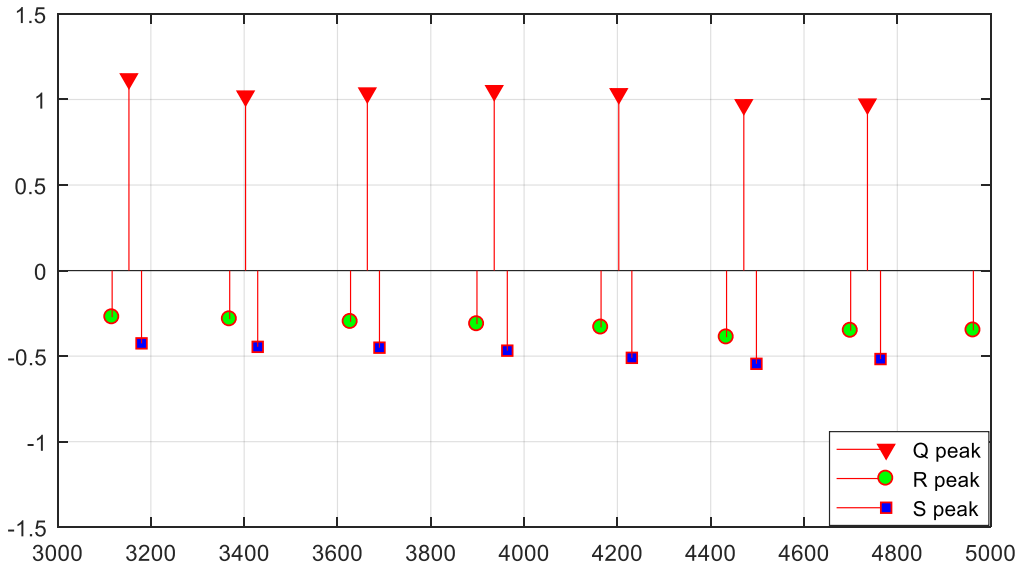


Figure 4.4: Detected QRS Points from the ECG Signal by Thresholding on FS2 Algorithm Applied Data

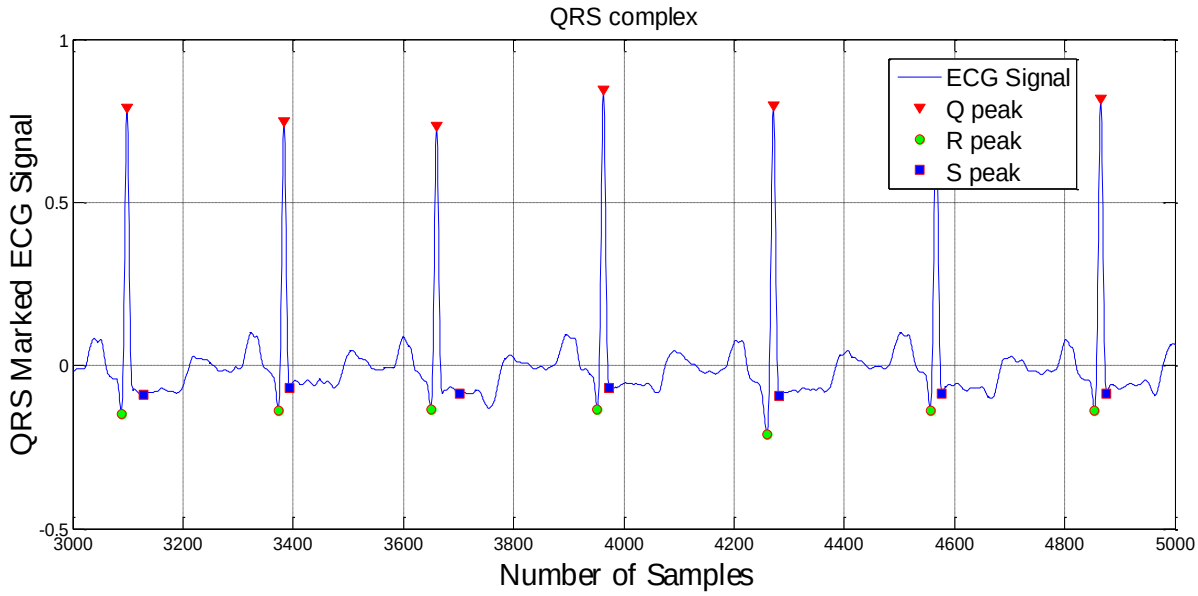


Figure 4.5: QRS Location Identification by FS2 Algorithm

4.5 S-T Segment Estimation and J-K Point Finding

The ST segment is the most important feature of the ECG for investigating angina pectoris. 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 Ischemia around the applied lead. S wave is the last wave in QRS complex. Since the QRS complex is already detected by the previous algorithm the S wave can be found through the minimum value in the range R_{loc}+5 to R_{loc}+50 [11]. On the other hand, T wave can be found between

the range R_{loc}+25 to R_{loc}+100 [11]. The ST segment is the most important feature of the ECG for investigating angina pectoris. The ST interval is measured from the J point (the minimum point of S wave) to the end of the T wave (which is also known as K point). The elevation and depression of ST segment together with the T-wave changes indicate the zone of ischemia around the applied lead. First we identified the J point and T- onset. Then average amplitude between J point and T-onset is calculated.

A similar method is developed for the detection of ST segment level. First we identified the J point and T-onset. Then average amplitude between J point and T~ onset is calculated using MATLAB. Detected J and K point in ECG signal in given in Figure 4.5. In addition with that the corresponding S and T points are also identified by the algorithm given in Figure 4.6.

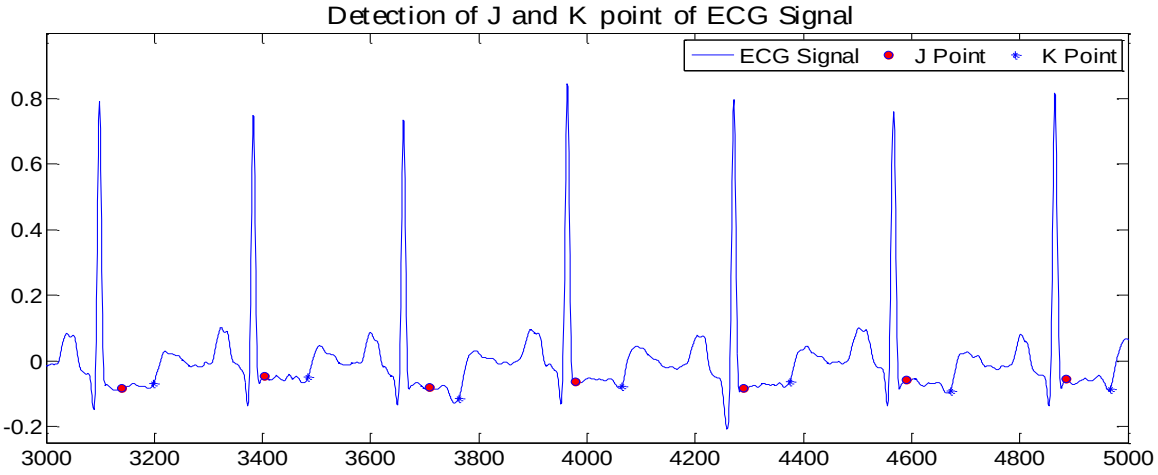


Figure 4.6: J and K point identification by the proposed method

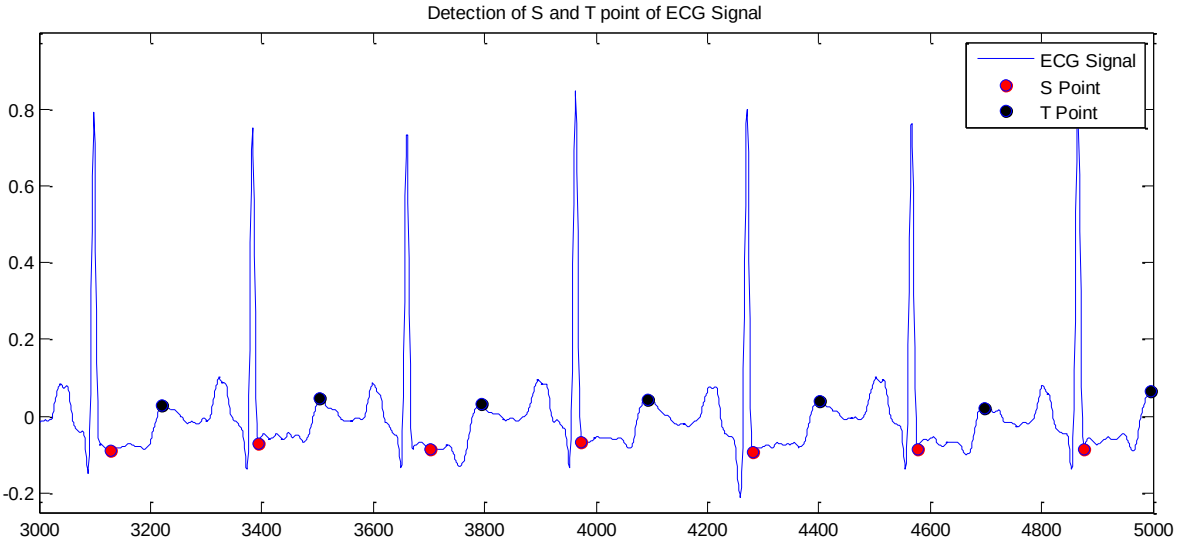


Figure 4.7: S and T Point Identification by the Proposed Method

4.6 Performance Measurement of the Algorithm

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. A band selection method is developed for the detection of isoelectric level detection. Result obtained from QRS detection technique i.e., the magnitude of R-peak is also known as first maxima of the ECG signal. 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 ischemiaa). 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 65 degree measured from vertical line, it is considered as negative ST deviation or ST depression [12]. The second rule classifies beat as ischemic if ST deviation is more than 0.08mv 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: *st_avg*=-0.4951 mv and *iso_avg* = -0.4060. When subtracted gives the result -0.0891 mv which shows that ST segment is deviated below the isoelectric line and hence it is considered as ST depression or negative ST deviation.

Using our proposed algorithm designed in MATLAB environment, normal and affected patient's ECG signal from MIT arrhythmia database are analyzed for evaluating the adeptness of the proposed algorithm. The results of different ECG signals of MIT arrhythmia database by our proposed algorithm are presented gradually. Here, ECG signals named by ecg105, ecg112, ecg113, ecg114, ecg115, and ecg119 in MIT-Arrhythmia database are tested.

For data 100_1:

Total ST Segment present in signal = 65

Total ST Segment Detected by the proposed method = 64

Total Abnormal ST Segment present in the Signal = 51

Total Abnormal ST Segment detected by the proposed method=50

For data ecg100_2:

Total ST Segment present in signal = 64

Total ST Segment Detected by the proposed method = 64

Total Abnormal ST Segment present in the Signal = 15

Total Abnormal ST Segment detected by the proposed method=13

For data ecg105:

Total ST Segment present in signal = 69

Total ST Segment Detected by the proposed method = 69

Total Abnormal ST Segment present in the Signal = 55

Total Abnormal ST Segment detected by the proposed method=52

For data ecg109:

Total ST Segment present in signal = 82

Total ST Segment Detected by the proposed method = 82

Total Abnormal ST Segment present in the Signal = 75

Total Abnormal ST Segment detected by the proposed method=74

For data ecg111:

Total ST Segment present in signal = 61

Total ST Segment Detected by the proposed method = 61

Total Abnormal ST Segment present in the Signal = 5

Total Abnormal ST Segment detected by the proposed method=5

For data ecg112:

Total ST Segment present in signal = 75

Total ST Segment Detected by the proposed method = 75

Total Abnormal ST Segment present in the Signal = 75

Total Abnormal ST Segment detected by the proposed method=72

For data ecg113:

Total ST Segment present in signal = 48

Total ST Segment Detected by the proposed method = 48

Total Abnormal ST Segment present in the Signal = 30

Total Abnormal ST Segment detected by the proposed method=37

For data ecg114:

Total ST Segment present in signal = 46

Total ST Segment Detected by the proposed method = 46

Total Abnormal ST Segment present in the Signal = 21

Total Abnormal ST Segment detected by the proposed method=21

For data ecg115:

Total ST Segment present in signal = 34

Total ST Segment Detected by the proposed method = 34

Total Abnormal ST Segment present in the Signal = 20

Total Abnormal ST Segment detected by the proposed method=22

For data ecg119:

Total ST Segment present in signal = 22

Total ST Segment Detected by the proposed method = 22

Total Abnormal ST Segment present in the Signal = 22

Total Abnormal ST Segment detected by the proposed method=23

In addition, how good the test is at detecting disease and normal conditions are the other important evaluating measurands of the proposed algorithm which can be found by calculating sensitivity and specificity, respectively.

Table 5.1: MIT Database ECG Signal and Their Angina Calculating Results by Proposed Method

Data ID	Detected Normal	Detected Angina	Actual Angina	Accuracy %	Sensitivity %	Specificity %
ecg100_1	12	52	51	96.8%	98.4%	-
ecg100_2	51	13	15	88.57%	96%	86.6%
ecg105	**14**	**55**	52	91.7%	82.3%	87%
ecg109	**8**	**75**	75	100%	100%	100%
ecg111	56	5	5	100%	100%	100%
ecg112	**3**	**72**	75	92.6%	-	96%
ecg113	**11**	**37**	30	85.4%	61%	100%
ecg114	**25**	**21**	21	100%	100%	100%
ecg115	**34**	**22**	20	96.4%	94.4%	100%
ecg119	**22**	**22**	23	97.7%	100%	95.6%
			Average=	**94.9%**	**83.2%**	**86.5%**

4.7 kNN based Results Comparing Multiple Features

It is already stated that the only one feature cannot be criteria to take decision. Therefore, with comparing multiple features, kNN based classifier has been trained with normal and abnormal features of S-T segments of each beat of the ECG signal. At first we have collected 30 normal S-T segments and 50 abnormal S-T segments. From these segmented signals, four features (mean, slope, standard deviation, and energy) have been extracted and trained the kNN classifier as to predict the nature of normal and abnormal property of ECG S-T segment.

If we have a time series of N number of samples, we can define it by $x(n)$. The mean of $x(n)$, $\bar{x}$ can then be calculated as,

$$\bar{x} = \frac{1}{N}\sum_{n=1}^{N} x(n) \tag{4.1}$$

Similarly, the variance, σ^2 is calculated as,

$$\sigma^2 = \frac{1}{N}\sum_{n=1}^{N} (x(n) - \bar{x})^2 \tag{4.2}$$

On the other hand the slope is calculated from the linear fit of the data points found in the given series $x(n)$. If a set of data from the time series $x(n)$ is fitted with the line $y=mx+c$ according to the least square error method, then the slope of the series is m. Here, c is the value of the intersecting point at $x(0)$ in y axis.

From the ECG signal, we have separated all the S-T segments and then the features have been extracted. Some normal and abnormal conditioned S-T segments were separated manually due to train the classifier. Here, in Table 5.2 the normal and abnormal features are given to understand the actual variation in the features space of the normal and abnormal ST segment of ECG signal. From the features given in Table 5.2 we have found that the ST segment of the abnormal ECG beat has the negative slope with a larger value, on the other hand normal ST segments often have the slopes with positive values. With the help of the feature given in the following table the kNN classifier has been trained so that it could be able to differentiate the normal and abnormal ECG beat due to the effect of angina pectoris.

Table 5.2: The Features of ST Segment of Normal and Abnormal ECG Beats

Normal		Abnormal	
Mean	Slope	Mean	Slope
0.009833716	24.50616226	-0.39603527	-10.04525523
0.005684072	4.862902914	-0.393569051	-5.191257296
0.006982667	10.57859212	-0.375209831	24.50616226
0.010334927	7.071581788	-0.39352189	-12.5834204
0.006378143	12.70634776	-0.376704307	-7.728431459
0.011322645	29.92852716	-0.373603756	-4.210078173
0.006868976	3.658288975	-0.43102001	-6.23924728
0.006036852	8.132240927	-0.389620217	-11.75357488
0.008641687	10.64478521	-0.36154266	-11.96536461
0.007925123	15.79928435	-0.338814341	-15.29875133
0.007527695	-3.457801299	-0.374954786	-5.213945474
0.006871627	-1.104919887	-0.345456669	-4.363820326
0.004489381	-0.920036659	-0.348667071	-14.01307862
0.011803097	-2.724648073	-0.39862241	-15.23870343

After the training with given data set, a small set of testing data has been applied to check the networks response with respect to its different distance calculating procedures of the nearest neighbors. The results of the testing performance are given in Figure 4.8. From the figure, we

have found that the query points for the testing points and their distance calculating through Mikowski and Chebyshev distance have the same effect.

In addition to that, by the kNN based trained network we have checked the classification accuracy, sensitivity, and specificity of all the ECG signals. These results are based on the property of ST segments of all the beats of a signal. The **data 100_1** of Arrhythmia data base have been checked by the proposed method and found the abnormal ST segments are 50 in that signal where the actual is 51. Therefore the classification accuracy is 98%, specificity= 98%, and sensitivity 100%. The result is given in Figure 4.9.

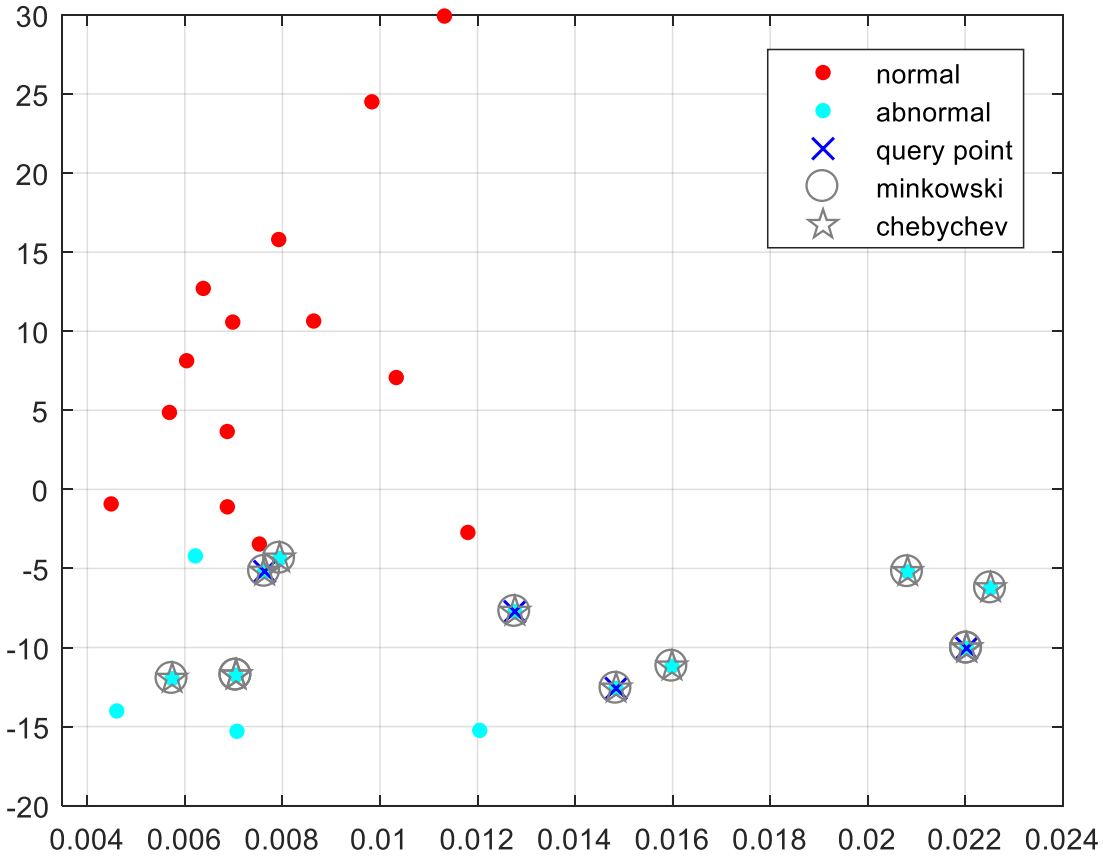


Figure 4.8: Testing the kNN model for best distance calculation procedure

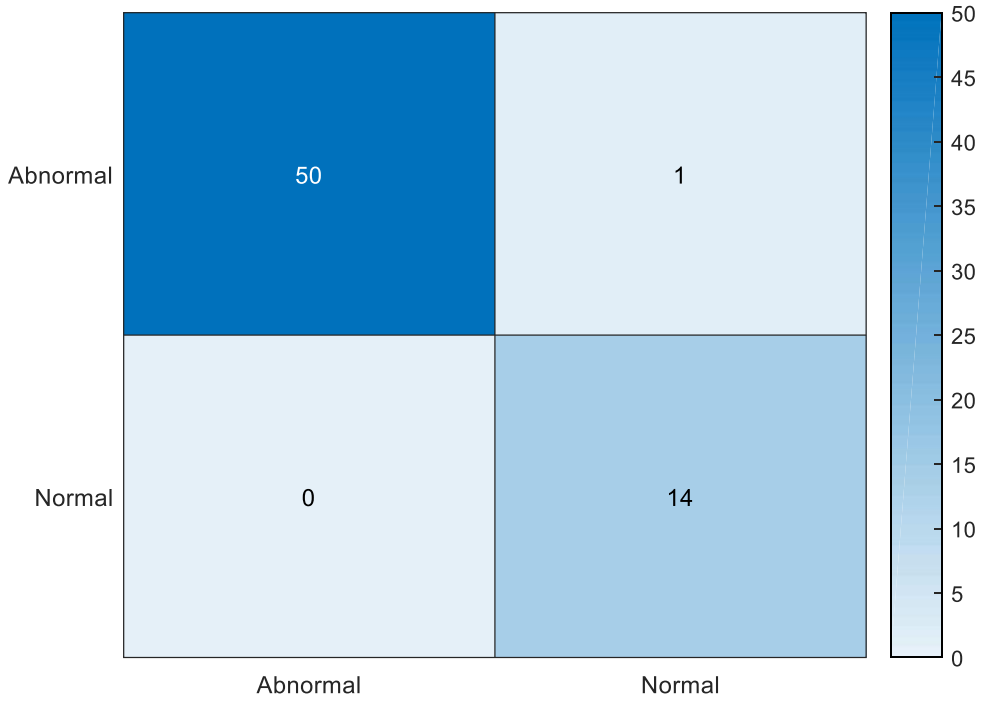


Figure 4.9: Confusion matrix of classification of normal and abnormal S-T segment of a single patient

All the results found by the kNN classifiers are given at the following Table 5.3 with the other information like accuracy, sensitivity, and the specificity of the proposed algorithms.

Table 5.3: MIT Database ECG Signal and Their Angina Calculating Results by kNN Classifiers

Data ID	Detected Normal	Detected Angina	Actual Angina	Accuracy %	Sensitivity %	Specificity %
ecg100_1	14	50	51	98%	98%	100%
ecg100_2	51	15	15	95%	100%	86.6%
ecg105	14	51	52	93.7%	95%	87%
ecg109	8	75	75	100%	100%	100%
ecg111	56	5	5	100%	100%	100%
ecg112	3	72	75	92.6%	-	96%
ecg113	15	30	30	91.4%	88%	100%
ecg114	25	21	21	100%	100%	100%
ecg115	34	22	20	96.4%	94.4%	100%
ecg119	22	22	23	97.7%	100%	95.6%
			Average=	**96.48%**	**97.2%**	**96.5%**

4.8 Chapter Summary

In this chapter, the classification accuracy, sensitivity, and the specificity of the proposed algorithms were tested. The performances of the algorithms have been found satisfactory to predict the angina pectoris from the ECG signals.

CHAPTER 5: Conclusions

5.1 Conclusions

5.2 Future Perspective

5.1 Conclusions

In this paper, we have proposed a method to detect angina pectoris from ECG signal. In this method additionally we have used baseline wandering correction that makes the method more correct in angina pectoris detection. From the results we get in average 94.9% accuracy, sensitivity 83.2%, and specificity 86.5%. In addition with the help of kNN classifier we have checked the classification accuracy of the proposed method based on four features. From the classification results, we have found that the proposed system can classify the normal and abnormal ECG beat based on the features of S-T segment with 96.48% classification accuracy, 96.5 % specificity and 97.2% sensitivity. From this point of view, we can conclude the resulting information that the kNN classifier can classify the abnormal condition of ECG beats more accurately. We believe that this method will be helpful for computerized analysis of ECG data in the field of angina pectoris detection which will be supportive for the doctors in diagnosis as well.

5.2 Future Perspective

Though MIT data base is used to calculate the results, for any ECG data with similar sampling frequency, this method will work appropriately. It can be a future direction to match the algorithm for different sampling rate considering a ratio based approach in peak detection problem. Eventually, if the sample matching algorithm can be implemented all types of ECG signal can be analyzed through this algorithm with its prior information about the sampling rate. It is also mentionable that there are nine different algorithms to find the peaks from ECG signal. Here, only FS2 algorithm has been used. Therefore, the other peak detection algorithms can be used to check the performance.

Additionally, other classifiers can also be applied to improve the performance of the algorithm. Someone can also design a MATLAB based graphic user interface (GUI) program using the proposed algorithms which can be more user friendly to detect angina pectoris from ECG signal.

References

[1] B. Malia, S. Zulj, R. Magjarevic, D. Miklavcic, and T Jarm, "Matlab-based tool for ECG and HRV analysis," *Biomedical Signal Processing and Control*, vol. 10, pp. 108–116, 2014.

[2] WHO Report 2015 available in: http://www.who.int/mediacentre/factsheets/fs310/en/

[3] COURAGE Trial Research Group. "Optimal medical therapy with or without PCI for stable coronary disease," *New England Journal of Medicine*, vol. 356, no. 15, pp. 1503-1516, 2007.

[4] Principles of critical care. New York: McGraw-Hill, Health Professions Division, 1998.

[5] K. Fox, M. A. A. Garcia, Madrid, D. Ardissino, P. Buszman, P. G. Camici, F. Crea, C. Daly, G. D. Backer, P. Hjemdahl, J. L. Sendon, J. Marco, J. Morais, J. Pepper, U. Sechtem, M. Simoons, Rotterdam, and K. Thygesen, "Guidelines on the management of stable angina pectoris: executive summary," *European Heart Journal*, vol. 27, pp. 1341–1381, 2006.

[6] C. Papaloukas, D. I. Fotiadis, A. Likas, L. K. Michalis, "An ischemia detection method based on artificial neural networks," *Artificial Intelligence in Medicine*, vol. 24, pp. 167-178, 2002.

[7] A. Khemphila and V. Boonjing, "Heart disease classification using neural network and feature selection," *2011 21st International Conference on Systems Engineering*, Las Vegas, NV, 2011, pp. 406-409.

[8] V. Seenivasagam and R. Chitray, "Myocardial infarction detection using intelligent algorithms," *Neural Network World*, vol. 26, no. 1, pp. 91-110, 2016.

[9] J. F. Wu, Y. L. Bao, S. C. Chan, H. C. Wu, L. Zhang, and X. G. Wei, "Myocardial infarction detection and classification — A new multi-scale deep feature learning approach," *IEEE International Conference on Digital Signal Processing (DSP)*, Beijing, 2016, pp. 309-313.

[10] J. Kojuri, R. Boostani, P. Dehghani, F. Nowroozipour, and N. Saki, "Prediction of acute myocardial infarction with artificial neural networks in patients with nondiagnostic electrocardiogram," *Journal of Cardiovascular Disease Research*, vol. 6, no. 2, 2015.

[11] M. Kumar, R. B. Pachori, and U. R. Acharya, "Automated diagnosis of myocardial infarction ECG signals using sample entropy in flexible analytic wavelet transform framework," *Entropy*, vol. 19, no. 488, pp. 1-14, 2017

[12] P. A. Iaizzo, Handbook of cardian anatomy, physiology, and devices, 3rd Edition, Humana Press, New Jersey, 2005.

[13] R. H. Whitaker, "Anatomy of the heart," *Medicine*, vol. 46, no. 8, pp. 423-426, 2018.

[14] Available in: https://www.nottingham.ac.uk/nursing/practice/resources/cardiology/function/conduction.php

[15] R. Gutierrez-Rivas, J. J. García, W. P. Marnane, and Á. Hernández, "Novel real-time low-complexity QRS complex detector based on adaptive thresholding," *IEEE Sensors Journal*, vol. 15, no. 10, pp. 6036–6043, 2015.

[16] A. Diker, Z. Comert, and E. Avci, "Diagnostic model for identification of myocardial infarction from electrocardiography signals," *Bitlis Eren University Journal of Science and Technology*, vol. 7, no. 2, pp. 132-139, 2017.

[17] S. Nilsson, M. Scheike, D. Engblom, L. G. Karlsson, S. Mölstad, I. Åkerlind, K. Örtoft, and E. Nylander, "Chest pain and ischaemic heart disease in primary care," *British Journal of General Practice*, vol. 53, no. 490, pp. 378–382, 2003.

[18] L. M. Buja and J. Butany, Cardiovascular Pathology, 4th Edition, Academic Press, Elsevier, 2015.

[19] J. L. Hinkle and K. H. Cheever, Brunner and Suddarth's Textbook of Medical-Sergical Nursing, 14th Edition, Wolters Kluwer, 2017.

[20] K. Fox, M. Angeles, A. Garcia, D. Ardissino, et. al., "Guidelines on the management of stable angina pectoris: A task force on the management of stable angina pectoris of the European Society of Cardiology," *European Heart Journal*, vol. 27, no. 11, pp. 1341-81, 2006.

[21] P. Gawrońs, K. Saeed, and K. Kułakowski, "Early warning of cardiac problems in a crowd," *Agent and Multi-Agent Systems: Technologies and Applications*, Lecture Notes in Computer Science, vol 6071, Springer, 2010.

[22] C. Ginghina, C. Ungureanu, A. Vladaia, B. A. Popescu, and R. Jurcut, "The electrocardiographic profile of patients with angina pectoris," *Journal of Medicine and Life***,** vol. 2, no.1, pp. 80-91, 2009.

[23] R. J. Gibbons, J. Abrams, K. Chatterjee, J. Daley, P. C. Deedwania, J. S. Douglas, et. al., "ACC/AHA 2002 guideline update for the management of patients with chronic stable angina : a report of the American College of Cardiology /American Heart Association Task Force on Practice Guidelines (Committee to Update the 1999 Guidelines for the Management of Patient with Chronic Stable Angina)," *Journal of American College of Cardiology*, vol. 41, no. 1, pp. 159- 168, 2003.

[24] M. A. Rahman, M. M. Haque, A. Anjum, F. Khanam, and M. Ahmad, "Baseline wandering removal from ECG signal by wandering path finding algorithm," *International Conference on Electrical Information and Communication Technology (EICT)* 2017, December, Khulna, Bangladesh, pp. 1-5.

[25] K. Minami, H. Nakajima, and T. Toyoshima, "Real-time discrimination of ventricular tachyarrhythmia with Fourier- transform neural network," *IEEE Transactions on Biomedical Engineering* vol. 46, no. 2, pp. 179–185, 1999.

[26] U. R. Acharya, A. Kumar, P. S. Bhat, C. M. Lim, and S.S. Lyengar, "Classification of cardiac abnormalities using heart rate signals," *Medical & Biological Engineering & Computing*, vol. 42, no. 3, pp. 288–293, 2004.

[27] P. W. Kamen, H. Krum, and A. M. Tonkin, "Poincare plot of heart rate variability allows quantitative display of parasympathetic nervous activity," *Clinical Sciences*, vol. 91, pp. 201-208, 1996.

[28] H. J. Blinchikoff and A. I. Zverev, Filtering in the Time and Frequency Domains, Noble Publishing, 1976.

[29] S. P. Wilkinson, M. Bernardi, I. K. Smith, T. P. Jowett, J. D. Slater, and R. Williams, "Effect of beta adrenergic blocking drugs on the renin-aldosterone system, sodium excretion, and renal hemodynamics in cirrhosis with ascites," *Gastroenterology*, vol. 73, pp. 659-63, 1977.

[30] http://www.picosecond.com/objects/AN-7a.pdf

[31] R. A. Haddad and A.N. Akansu, "A class of fast gaussian binomial filters for speech and image processing," *IEEE Transactions on Acoustics, Speech and Signal Processing*, vol. 39, pp 723-727, 1991.

[32] L. G. Shapiro and G. C Stockman, Computer Vision, Prentence Hall, 2001.

[33] M. S. Nixon and A. S. Aguado, Feature Extraction and Image Processing. Academic Press, 2008.

[34] V. K. Ingle and J. G. Proakis, Digital Signal Processing Using MATLAB, Third Edition, Cengage Learning, Stamford, CT 06902, USA, 2012.

[35] M. Weeks, Digital Signal Processing: Using MATLAB and Wavelets, Infinity Science Press, 2007.

[36] J. L. Semmlow, Biosignal and Biomedical Image Processing: Matlab Based Application, Marcel Dekker Inc., 2004.

[37] S. W. Smith, Digital Signal Processing, 2nd Edition, California Technical Publishing, San Diego, California, USA, 1999.

[38] R. J. Gibbons, J. Abrams, K. Chatterjee, J. Daley, and S. V. Williams, "ACC/AHA 2002 guideline update for the management of patients with chronic stable angina," *Journal of American College of Cardiology*, vol. 41, no. 1, pp. 159- 168, 2003.

[39] R. A. Balda, G. Diller, E. Deardorff, J. Doue, and P. Hsieh, "The HP ECG analysis program," *Trends in Computer processed Electrocardiograms*. North Holland, Amsterdam, pp. 197–205, 1977.

[40] M. L. Ahlstrom and W. J. Tompkins, "Automated high-speed analysis of holter tapes with microcomputers," *IEEE Transaction on Biomedical Engineering*, vol. 30, pp. 651-657, 1983.

[41] M. J. Vidya and D. Kayaa, "Analysis of ECG signal using MATLAB for the detection of ischemia," *International Journal of Innovative Research & Development*, vol. 2, no. 4, pp. 308-319, 2013.

[42] R. V. Andreaol, B. Dorizzil, J. Boudyl, and I. C. M. Mota, "ST-Segment analysis using hidden markov model beat segmentation: Application to ischemia detection," *Computers in Cardiology*, vol. 31, pp. 381-384, 2004.

[43] G. B. Moody and R. G. Mark, "The impact of the MIT-BIH arrhythmia database," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, pp. 45-50, 2001.

List of Publications

M. M. Islam[1] and A. B. M. A. Hossain[2], "Angina pectoris detection using ECG signal," *Proceedings of 14th Global Engineering and Technology Conference*, 29-30 December 2017, BIAM Foundation, Dhaka, Bangladesh, pp. 1-11.