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EKG Tracking for Augmented Standardized Patient Virtual Pathology Stethoscope Heart Auscultation

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EKG TRACKING FOR AUGMENTED STANDARDIZED PATIENT VIRTUAL PATHOLOGY STETHOSCOPE HEART AUSCULTATION

by

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ABSTRACT

EKG TRACKING FOR AUGMENTED STANDARDIZED PATIENT VIRTUAL PATHOLOGY STETHOSCOPE HEART AUSCULTATION

Sujith Surendran
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In recent years, a lot of research has focused on improving the clinical skills of medical students and medical practitioners using standardized patients. Standardized patients (SP's) are used by the medical students and physicians in place of mannequins for a more realistic experience. SP's are real people trained to simulate specific illnesses and conditions to a high degree of accuracy which makes it difficult for the medical students to distinguish them from real patients. This research will enhance the capabilities of the standardized patients by providing a non-invasive, natural, harmless and realistic appearing tracking method for placing virtual pathologies using stethoscopes. This method of tracking the stethoscope head involves analyzing and processing the electrical activities of the heart which can be implemented in augmented stethoscopes for auscultation of normal and abnormal cardiac diseases. The electrocardiogram (EKG) signals are processed to obtain heart beat signals called QRS complexes that are then classified to determine the correct position on a SP's torso. This improves the capabilities of the augmented standardized patients in providing a realistic heart auscultation scenario to the medical students. Moreover it is cost effective and appropriately classifies the signal.

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CHAPTER 1

INTRODUCTION

1.1 Overview

Heart disease and strokes are among the top causes of death in the United States, accounting for more than 35% of all deaths [1]. Each day in the United States alone, 2400 people die, an average of one death every 34 seconds [1]. According to a study conducted by the Chronic Disease Prevention and Health Promotion, more than 870,000 Americans die of heart disease and stroke every year, and it is believed that more than 80 million Americans live with one or more types of heart disease [1]. Contrary to the general belief that heart diseases are common among older adults, the statistics show that more than 148,000 (17%) of Americans who died of cardiovascular diseases in 2004 were younger than 65 years of age [1]. Heart disease is the major cause of disability and is considered to be most preventable.

Heart disease or cardiovascular disease is a broad term for the different diseases affecting the heart. There are many different forms of heart disease. Coronary heart disease is the most common type of cardiovascular disease. It occurs when the coronary arteries that supply oxygenated rich blood to the heart muscle, become hardened and narrowed due to the buildup of plaque on the inner walls of the arteries. Plaques are a mixture of fat, cholesterol, calcium and other substances found in blood. Coronary heart disease is a disorder of the blood vessels of the heart, which can lead to a heart attack and many other serious conditions which include stroke, high blood pressure, rheumatic heart

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The reference model for this work is *IEEE Transactions on Signal Processing*

disease and angina (chest pain). A heart attack occurs when the plaque ruptures and causes blood clots, preventing oxygen and nutrients from getting to the heart.

There are new challenges in the field of health sciences due to the existing and emerging new technology for medical education. Some of them are difficult for medical students to understand and hence need appropriate clinical training. There has been much research and innovative findings to support the clinical practitioners in decreasing medical errors and improving the quality of care provided to patients. This helps the medical students gain confidence, achieve appropriate performance and provide the best standards of care.

Standardized patients (SP's) are being used by medical students and physicians instead of mannequins for better training that provides the feel of a realistic environment. Standardized patients are real people trained to portray patients with a high degree of accuracy in order for a medical student to practice and improve certain aspects of clinical training such as performing a physical examination, eliciting a history and doctor-patient communication [2]. Many schools these days use standardized patients for teaching and testing the communication skills in students. Despite the advantages over real patients, standardized patients are time and resource expensive when it comes to teaching and testing clinical skills.

1.2 Thesis Statement

This research will enhance the capabilities of the standardized patients (SP's) by providing a non-invasive, natural, harmless and realistic tracking method for placing virtual pathologies by using stethoscopes. This method of tracking the stethoscope head

involves analyzing and processing the electrical activities of the heart which can be implemented in augmented stethoscopes for auscultation of normal and abnormal cardiac diseases. The result is a method that can be used by medical students for enhanced clinical training.

1.3 Problem Statement

Tracking the stethoscope head by using electrical activities of the heart is a new concept and little research has been done in this field. Much of the previous research has focussed on analyzing and processing the sounds generated by the heart. Reynel Castelino and Dr. Frederic D. McKenzie [2] designed and implemented an electronic stethoscope with tracking capability for medical students, to find the abnormalities in the heart using standardized patients. A magnetic sensor is placed at the head of the electronic stethoscope for tracking the location information and it allows the standardized patients to appropriately trigger the abnormal heart signal. The output sound from the electronic stethoscope is recorded corresponding to a particular medical condition. The magnetic sensor is complex, less accurate, and very costly. It is also susceptible to environmental issues, such as interference from strong electric currents and large pieces of metal. Therefore, a better and less expensive means of tracking the stethoscope head is needed. No one has yet attempted to track positions on the human torso using the electrical signals of the heart.

However, classification of normal and abnormal heart signals is a common research topic. For example, Jacques Pinard De Vos [3] designed an algorithm to assist physicians in decision making to classify the normal and abnormal heart sounds. The

heart sounds are preprocessed and classified using three feature selection algorithms. Differentiating between various types of murmurs was conducted with the direct ratio and wavelet methods. A neural network algorithm was used to validate the performance of these two methods. The disadvantage of using this algorithm is the limitation of its identification of systolic murmurs and misclassification of the normal sounds. The algorithm is valid only if the correlations between specific murmur types are the same for different patients with the same condition. Our algorithm will attempt to utilize classification methods such as these to track human torsos.

1.4 Solution

This research focuses on a system which can efficiently track the position of the stethoscope head by classifying the signals at the various positions of the heart. Only two leads are used to record the EKG signals from the heart at four different positions namely the mitral, tricuspid, pulmonary and aortic area. This method is a low cost, non-invasive, harmless and natural method of tracking the heart's electrical activities. The EKG signals are processed to obtain QRS complexes that are then classified to determine the correct position on a SP's torso. This improves the capabilities of the augmented standardized patients in providing a realistic scenario for the medical students.

1.5 Contributions

- A cost-efficient system is modeled, designed and implemented for accurate tracking of the stethoscope head by using the electrical activities of the heart.

- The EKG signal is recorded at four different positions namely the mitral, tricuspid, pulmonary and aortic area using the Welch Allyn Meditron analyzer. Only two leads placed side by side are being used instead of the standard three leads EKG system.
- The EKG signal is processed using the Butterworth low pass filter to remove the noise using MATLAB. We have implemented an algorithm for detection of QRS complexes using a paper by Pablo Gomez [4], on ***EKG Signal Processing: An Algorithm to detect and align QRS Complexes***.
- Each QRS complex in the EKG signal is plotted separately and their average QRS complex is also plotted.
- The values of RRavg (average R-R in seconds), RRdev (standard deviation of R-R in seconds) and RRppm (cardiac rhythm in pulses per minute) are recorded for all the signals.
- The duration between onset and offset(QS) and the peak amplitude (R) of the each QRS complez in the signal are used as features for classification.
- The QRS complexes are acccurately classified so as to locate the position of the EKG signal.

1.6 Thesis Organization

Chapter 2 introduces the concept of virtual reality, augmented reality, standardized patients and their use for medical students. The detailed description of the electrical conduction of the heart and the formation of Einthoven triangle using three leads are discussed later. The QRS curve which is the most important signal in the EKG

wave is also described. Chapter 3 presents an overview of the previous work in the tracking of the virtual stethoscope. Chapter 4 investigates the approach and method of tracking the virtual stethoscope using the electrical activities of the heart. This includes the detection and classification of the QRS complexes from the EKG signal. Chapter 5 summarizes the results, describes the data listings and plots the data for a better understanding. This is followed by the conclusion and the future research in chapter 6.

CHAPTER 2

BACKGROUND

2.1 Virtual reality

Virtual reality (VR) often referred to as Virtual Environments (VE), employ computer-generated, three-dimensional simulations in which the participant experiences and interacts with graphical models using a variety of specialized input and output devices, thereby producing the illusion of reality. These interactive devices such as headsets, goggles, body suits, gloves and trackers send and receive information. The user experiences a total immersion by means of excellent human computer interface through hardware and software [5]. VR is used in applications such as scientific and engineering research, aircraft pilot training, entertainment industry, military, construction designs, training medical personal for surgical procedures, computer games, prototype designs for new products, control of remote-control vehicles, medical analysis and training personal for working in hazardous environments or with costly equipment.

2.2 Augmented Reality

Augmented reality (AR) is a field of computer research which combines the features of virtual reality and the real world. AR supplements reality, rather than completely replacing it like virtual environments [6]. It uses devices like live video imagery, motion-tracking devices, head-mounted displays, sensors and actuators, and fiducial marker recognition. AR has its applications in maintenance and repair, robot path planning, entertainment, military, navigation devices, emergency services, enhanced

sightseeing, games, annotation and medical visualization. In medical applications, the doctors can collect three-dimensional datasets of patients in real time using non-invasive sensors like Magnetic Resonance Imaging (MRI), Computed Tomography scans (CT) and ultrasound imaging which can then be rendered and combined for an internal view of the patients without the need for an invasive surgery [6]. It is used in surgical rooms for the accurate location of the operation which reduces the trauma of an operation by using small incisions [6]. In short, doctors could actually use Augmented Reality for visualization and as a training aid for surgery. In recent developments, Augmented Reality is also used for tracking the movement of a stethoscope by using a magnetic sensor to augment a standardized patient. When the stethoscope reaches the desired location, it triggers a sound file to the examiner. This can be used by medical students to interact, communicate with and diagnose patients [2].

2.3 Standardized Patient

Standardized patients (SP's) are real people trained to portray patients in order for a medical student to practice and improve certain aspects of clinical training such as performing a physical exam, eliciting a history and doctor-patient communication [2]. They provide feedback after such encounters and are used in testing the clinical skills of the medical students. They are also used to train medical students to learn professional conduct and are at times sent unannounced in physician practices to evaluate standards of care. The standardized patients simulate specific illness and conditions to a high degree of accuracy which makes them difficult for the medical students to distinguish them from real patients.

Auscultation is a procedure of listening to sounds produced by the body for the diagnosis of diseases. Heart murmurs are the most common body sounds and correspond to abnormalities in the functioning of the heart. Medical students need the experience and skill to identify the heart murmurs and sounds. The principal instrument used for the clinical detection of heart sounds is the acoustical stethoscope. An improvement over the acoustic stethoscope, usually has low fidelity, is the electronic stethoscope consisting of a microphone, an amplifier and a head set [7]. Auscultation is the most commonly used technique in health care. So, standardized patients are used to train medical students to simulate heart and lung sounds, by manipulating blood pressure for heart conditions and breathing through one lung. However, it is often difficult to find healthy individuals who can realistically simulate various symptoms.

2.4 The Electrocardiogram (EKG)

As mentioned earlier, heart diseases and strokes are the main causes of death in the United States. EKG analysis is the most common way to study and diagnose heart diseases. The heart is a muscle that works continuously, much like a pump. Each beat of the heart is set in motion by an electrical signal from within the heart muscle. Figure 2.1 shows the four internal chambers of the heart. An electrocardiogram (EKG), invented by Dr. Willem Einthoven in 1902, measures the electrical activity of the heart on the surface of the body. An electrocardiogram indicates the conduction of electrical impulses through the heart, and it measures and records both the intensity of the electrical activity and the time interval involved [8]. In other words, "the electrocardiogram (EKG) is a time-varying signal reflecting the ionic current flow which causes the cardiac fibers to contract

and subsequently relax" [9]. The surface EKG is obtained by recording the potential difference between two electrodes placed on the surface of the skin. These waveforms indicate whether the heart is healthy or undergoing a cardiac attack. EKG interpretation refers to both the heart's electrics and cardiac mechanics. It still remains a non-invasive, quick and effective diagnostic tool despite advanced technological advancement in the field of health sciences [10].

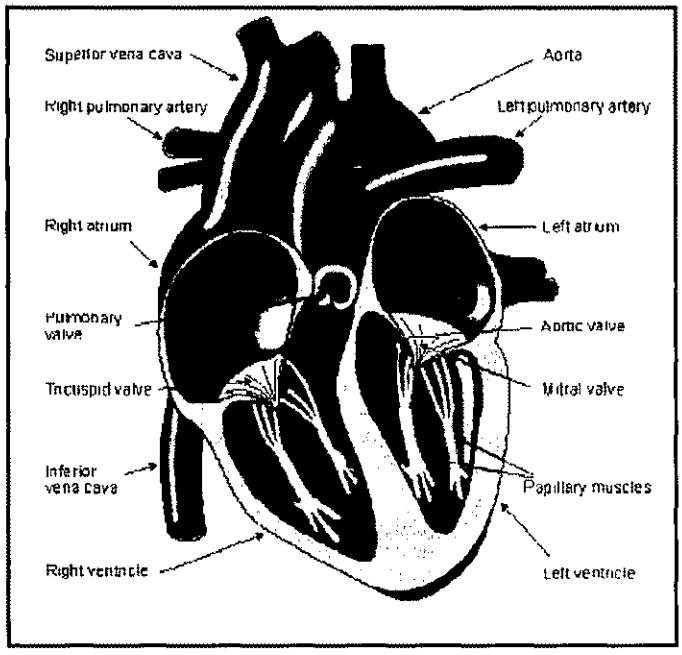

Figure 2.1: Cross section of the heart [11].

Each beat of the heart begins with an electrical signal from the sinoatrial node (SA node) located in the heart's right atrium as shown in the figure 2.2. When the heart's right atrium is full of blood, the electrical signal spreads across the cells of the heart's right and left atria which cause the atria to contract or squeeze. This pumps blood through the open valves from the atria into both ventricles [11]. The P wave on the EKG marks

the contraction of the heart's atria [12]. The conduction system of the heart with the basic nodes is shown in figure 2.3.

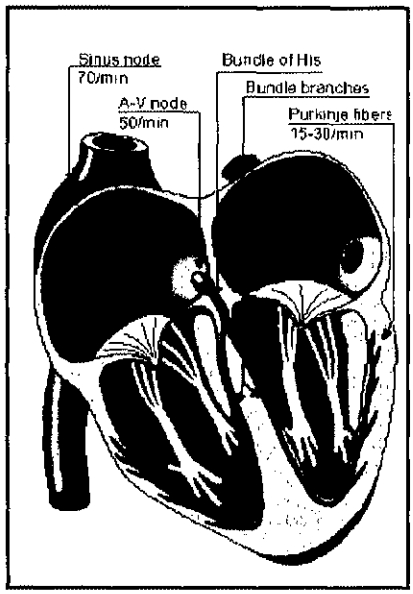

Figure 2.2: Conduction system of the heart [11].

The signal arrives at the atrioventricular (AV) node near the ventricles. Here it is slowed for an instant to allow the heart's right and left ventricles to fill with blood. On the EKG, this interval is represented by the start of the line segment between the P and Q wave. The signal is released and moves next to the bundle of His, located in the heart's ventricles. From the bundle of His, the signal fibers divide into left and right bundle branches, which run through the heart's septum. On the EKG, this is represented by the Q wave. The signal leaves the left and right bundle branches through the purkinje fibers that connect directly to the cells in the walls of the heart's ventricles and spreads quickly across the heart's ventricles. As the signal spreads across the cells of the ventricle walls, both ventricles contract but not exactly at the same moment. The left ventricle of the

heart contracts an instant before the right ventricle. On the EKG, the R and S waves mark the contraction of the heart's left and right ventricles respectively[11, 12].

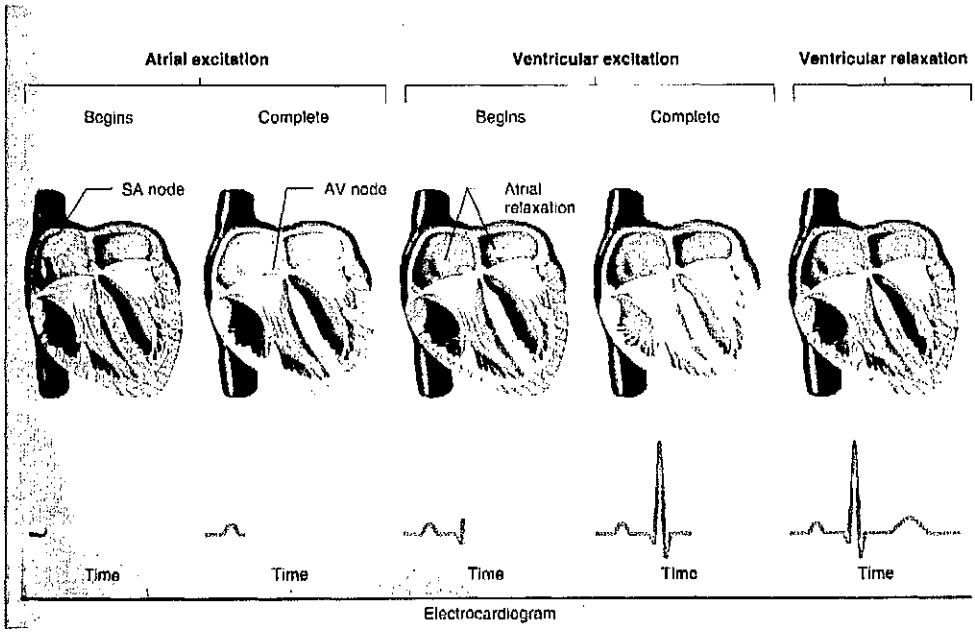

Figure 2.3: Electrical conduction of the heart [11].

The contraction of the heart's right ventricle pushes blood through the pulmonary valve to the lungs and the contraction of the heart's left ventricle pushes blood through the aortic valve to the rest of the body. As the signal passes, the walls of the heart's ventricles relax and await the next signal. On the EKG, the T wave marks the point at which the heart's ventricles are relaxing. The T wave is sometimes followed by the U wave, which is generated by the depolarization of different other muscles. This process continues over and over [11, 12].

The sequence of steps in the formation of EKG signal is illustrated using the figure 2.3. The EKG signal is characterized by the six peaks and valleys denoted by P, Q,

R, S, T and U waves, which repeats itself periodically to form a train of pulses. The EKG tracing for the single cardiac cycle is as shown in the figure 2.4.

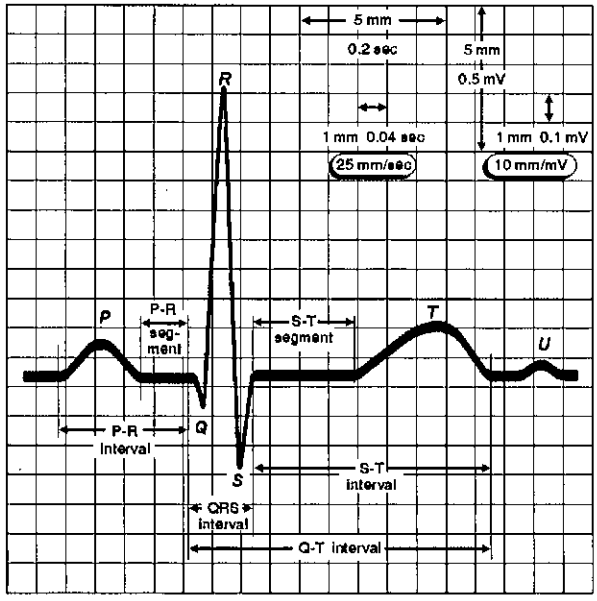

Figure 2.4: A typical lead II EKG signal [11].

It is possible to record the electrical activity of the heart by placing electrodes at specific points on the body. In 1902, William Einthoven was the first to record an EKG signal and for this he received the Nobel Prize in physiology or medicine in 1924. Even though there is a lot of research in this field, EKG signal remains the most important signal for finding the heart abnormalities. Three main methods have now been recognized for recording EKG signals from patients. The standard number of electrodes used for a diagnostic EKG is twelve, but as few as three electrodes are being used for monitoring EKG. The 12 lead EKG systems are commonly used in clinical applications. These leads can be grouped in three classes namely, the unipolar limb leads (aVR, aVL, aVF), the bipolar limb leads (I, II, III) and the chest leads (V1 to V6). Among the twelve leads, the

six leads: I, II, III, aVR, aVl, aVF originate from the same three measurement locations. This leads to the fact that any two of these six leads contain the exact information as the other four leads. However, all the 12 leads are required for recording the EKG signal for enhanced pattern recognition for more accurate diagnostic problems. The three lead EKG is generally used these days in telemetry monitoring, emergency departments and during medical procedures.

The electrodes should be placed appropriately because any slight disturbance causes the EKG to distort. An accurate indication of the cardiac vector can be provided by three electrodes connected at each of the vertices of the Einthoven triangle [9, 13] as shown in the figure 2.5. Signals from lead II, which is considered as the most significant and widely used for diagnosis of rhythm problems is a measure of the potential difference between the right arm and the left leg with the electrode of the left arm acting as ground. The Einthoven's limb lead I is defined as the potential difference between the left arm and right arm with the electrode at left leg acting as ground. The limb lead III is the potential difference between the left leg and left arm with the electrode at right arm acting as ground.

Recent research has shown that 2-lead EKG can replace 3-lead and 12-lead EKG [14]. This can be substituted to certain clinical and research application which pertains to the amplitude of the QRS complexes without any redundancy of the information from the 12-lead EKG. This was analyzed by considering the correlation and it was strong from all the three EKG systems [14]. The one or two lead system is used for monitoring long term or ambulatory patients. The EKG signal varies according to the position of the electrodes but certain features like P, Q, R, S, and T are always present.

A typical peak to peak EKG signal is in the order of 1 to 5 mV, which makes it susceptible to environmental noise and various other artifacts. The main sources of noise are power line noise, poor electrode contact noise, motion artifacts, muscle contraction noise, respiration, electromagnetic interface from other electronic devices and noise coupled from other electronic devices, usually at high frequencies [11].

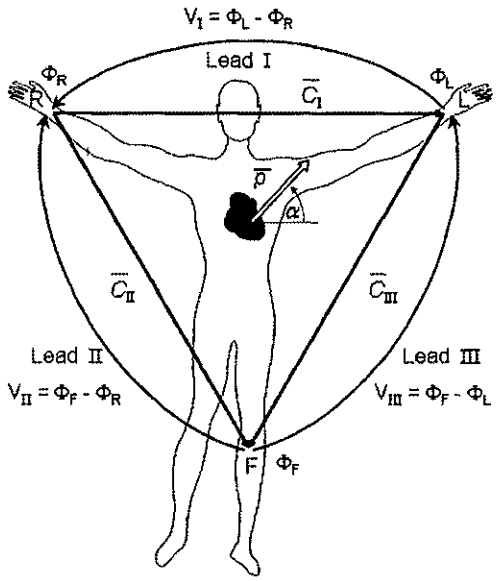

Figure 2.5: Limb leads and Einthoven triangle [11].

Power line noise consists of interference in the EKG by the 60 Hz pickup and harmonics from the nearby AC power supplies. Poor electrode contact is due to the loss of contact between the electrode and the skin which causes a baseline drift. Motion artifacts are caused due to the shift in the baseline with the changes in electrode skin impedance. Muscle contraction noise is caused by the contraction of other muscles besides heart and Respiration noise encourages a drift in the base line. It is important to filter these noises for the accurate detection of the EKG signal [11].

Table 2.1: Normal and abnormal parameters of EKG components [15].

EKG Components	Normal Parameters	Abnormal Parameters	Causes of abnormal parameters
P Wave	Upright in most leads including lead II. Duration: <0.11 sec. Amplitude: 0.5-2.5 mm.	Inverted Notched or tall	Junctional rhythm Atrial rhythm, atrial hypertrophy.
PR Interval	Duration: 0.12-0.20 sec.	Duration: shorter or longer than normal	Junctional rhythm, Wolff-parkinson-white syndrome
Q wave	Duration: <0.04 sec. Amplitude: 25% of the amplitude of the R wave.	Duration: <0.04 sec or longer. Amplitude: At least 25% of the amplitude of the R wave.	Myocardial infarction
QRS Complex	Upright, inverted or biphasic waveform Duration: <0.11 sec. Amplitude: 1 mm or more.	Duration: <0.11 sec or more.	Bundle branch block, ventricular ectopic i.e. PVC
QT Interval	Duration: less than ½ the width of the R-R interval.	Duration: at least ½ the width of the R-R	Long QT syndrome, hypothermia, cardiac

		interval.	drugs, subarachnoid hemorrhage. Short QT associated with hypercalcemia.
ST Segment	In line with PR or TP segment(baseline) Duration: shortens with increased heart rate.	Deviation of 0.5 mm or more from baseline.	Cardiac ischemia or infarction, ventricular hypertrophy, early repolarization, digoxin dip, pericarditis, subarachnoid hemorrhage.
T Wave	Upright, asymmetrical and bluntly rounded in most leads. Duration: 0.10-0.25 sec. Amplitude: less than 5 mm.	Peaked, inverted, biphasic, notched, flat or wide waveforms.	Cardiac ischemia or infarction, left-sided tension pneumothorax, hyperkalemia, left bundle branch block, subarachnoid hemorrhage, hypokalemia.
U Wave	Upright Amplitude: < 2mm.	Peaked or inverted Amplitude: > 2mm.	Hypokalemia, digoxin, cardiomyopathy, diabetes, ventricular hypertrophy, quinidine.

2.5 QRS curve

The QRS complex is the most striking waveform within the electrocardiogram due to the contraction of the heart. The direction of the QRS complex is generally not important for the EKG interpretation but the width is the key factor. The QRS complex represents the depolarization of the ventricles. It is being used for diagnosis because of the large amplitude and small width as compared to the rest of the signal. The large differences in the muscle mass of the atria and ventricles cause the difference in the amplitude of P and QRS wave. After locating the QRS complexes, it is easier to calculate the pulse and segment the signal into individual cycles or beats. This can further assist in locating the other characteristic waves of the EKG signal. The shape and duration of the QRS-complex provides information about the current state of the heart. The detection of the consecutive QRS complex allows determining the heart rate which can infer some of the heart problems [11]. Processing the EKG signal and detecting the QRS complex forms the key aspect in the real time analysis of EKG signal. Due to the various forms of noise associated with the EKG signal, it is difficult to detect the QRS complexes.

The duration of the QRS complex is usually about 50 to 100 ms, anything longer than this is an indication of bundle branch block [12]. The amplitude of the QRS complex depends on how synchronized the axis of the lead is with the direction of the current flow. The peak amplitude is at least one and half times the peak of T wave and twice the amplitude of the P wave. The onset and offset of the QRS complex can be found using the QRS detection algorithm, which gives the location and shape of the QRS complex. The shape and spacing between P and T waves, as well as QRS complex can be distorted to a great extent in some of the heart diseases. In certain diseases like Atrial enlargement

and myocardial infarction there is not much difference in the cardiac rhythm, but it affects the working of the heart muscle which in turn distorts the shape of the EKG. There are some diseases like atrioventricular (AV) block and tachycardia affecting the conduction tissue and triggering the ventricular fibrillation which decelerate and accelerate the cardiac rhythm respectively. The low and high heart rate can be about 30bpm and 240bpm depending on the cardiac rhythm. In the case of high heart rate it results in overlapping of the QRS complexes which in turn makes it difficult to find the onset and offset values of the QRS complex [8].

2.6 EKG Chip Circuit

Bobbie Patrick, in his research "Electrocardiogram (EKG) data acquisition and wireless transmission" had designed a bread board circuit to acquire the EKG signal which is being used in our research for real time acquisition of the heart EKG signals. Some of the design considerations are that the front end of the EKG chip circuit must have the capability to sense the low amplitude signals of the range 0.05–10 mV [13]. It should have very high input impedance (greater than 5 Mega-Ohms), flat frequency response (0.05-150 Hz), low input leakage current (less than 1 micro-Amp) and high common mode rejection ratio [13].

The electrodes are connected as the input to the instrumentation amplifier which is the front end of the bread board circuitry designed for EKG signal acquisition. It has high input impedance and very high Common Mode Rejection Ratio (CMMR) which is required for capturing the EKG signals [13]. The analogue device AD 624 shown in

figure 2.6 is primarily designed for use in bio-electronics due to its high precision and low noise. Connecting the pins 3, 11 and 13 provides with a gain of 1000 [13].

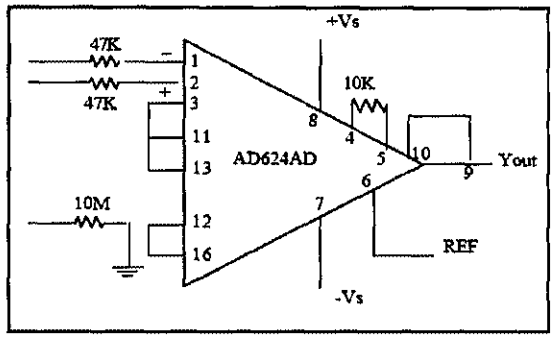

Figure 2.6: AD 624 connection diagram instrumentation amplifier [13].

After the EKG signals are amplified, it is then applied through the two stage filtering process. The first stage low-pass filtering shown in figure 2.7 was implemented as a cascaded RC or passive filters with a cut-off frequency of 150 Hz. The filter passes the low frequency signals and attenuates the frequencies higher than the cut of frequency. It is a non-inverting and has a gain of unity [13]. The cut off frequency was calculated by the equation,

$$f_c = 1/2(Pi)RC \qquad (1)$$

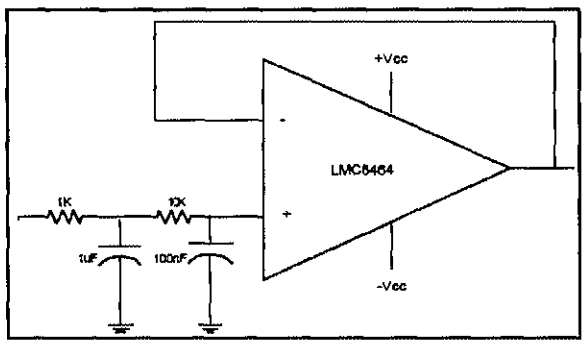

Figure 2.7 Low pass filter [13].

The impedance of the second stage which is a notch filter must be higher, since it provides the load for the first stage. A notch filter was implemented using Burr-Brown's Universal Active Filter (UAF42) which is a monolithic, time continuous, 2nd order active filter for simple and complex filter designs [13]. The auxiliary operational amplifier is used to sum both the high-pass and low-pass outputs to create a band reject (notch) filter. A 60 Hz notch filter is easily realized with the UAF42 and six external resisters as shown in figure 2.8. "At f= f_{NOTCH}, both of these output times their respective gain at the summing circuit are equal in magnitude but 180° out of phase. Hence, the output goes to zero" [13].

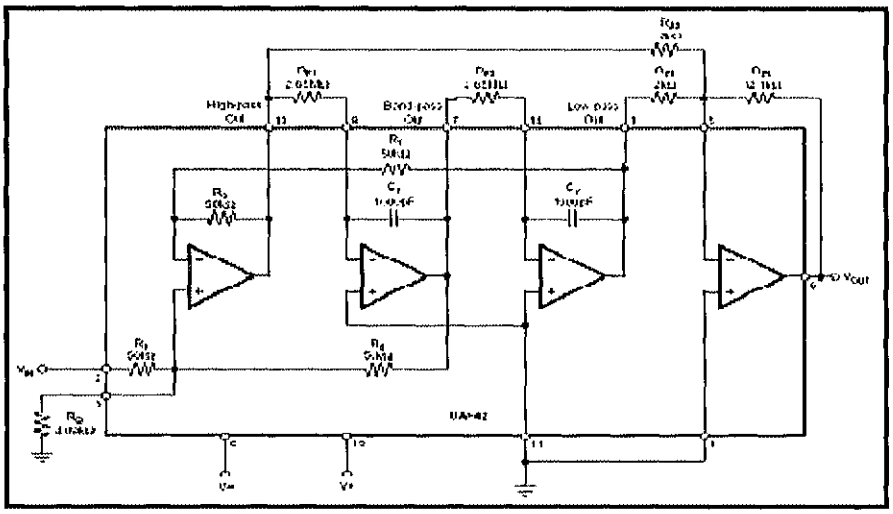

Figure 2.8: UAF42 realized as a 60 Hz Notch Filter [13].

The notch frequency is set by the following calculations:

$$f = (A_{LP}/ A_{HP}). (R_{Z2}/ R_{Z1}). f_o \quad (2)$$

In the equation (2), A_{LP} is the low pass output and A_{HP} is the high pass output. Typically, $A_{LP}/ A_{HP} = 1$ and $R_{Z2}/ R_{Z1} = 1$, which means $f = f_o$.

The most significant noise signal is due to the harmonics of 60 Hz AC mains interference and hence a notch filter is designed to get a high Signal-to Noise (S/N) ratio. Texas Instruments UAF42 was used because of its better attenuation and sharp notch curve control than other technologies which has resulted in noise reduction while amplifying the EKG signal [13].

After amplification and filtering, the signals are digitized by an analog-to-digital convertor (ADC). ADC requires the sampled values to fall completely within the positive voltage range. The summing amplifier shown in the figure 2.9 ensures the restraint in positive range.

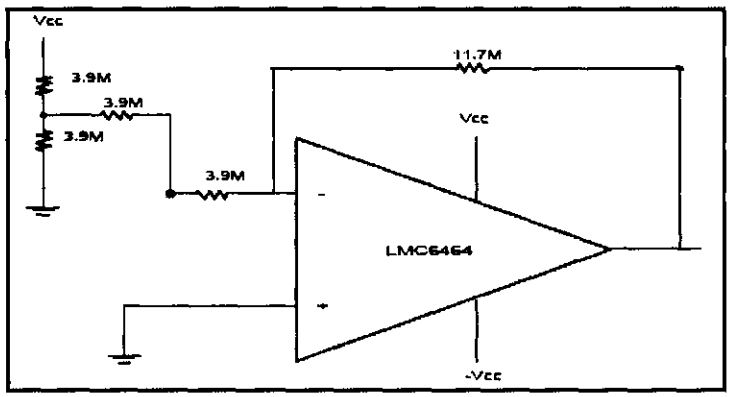

Figure 2.9: Summing amplifier [13].

The DC voltage, which is added to signal values, is supplied by the voltage divider circuit made with two 3.9 M-Ohm resisters. The other resisters set the gain of the amplifier to one, and they don't influence the voltage division. In this way the output of the summing amplifier is the EKG signals transposed up by the half of the supply voltage (Vcc = 5 Volts) [13].Analog devices ADUC831 data acquisition system which has a 12-

bit ADC is used for digitization of the EKG signal. This circuit can be used to acquire the heart EKG signals and then converting it to digital form for saving it in the database.

The main advantage of using this circuit is that it can be used to acquire the heart EKG signal with real time capabilities placing the electrodes at the stethoscope head and recording the signals. The disadvantage with the system is care should be taken while recording the signal, otherwise there would be lot of noises.

CHAPTER 3

RELATED WORK

With the growing errors by the clinical practitioners, it is a necessity to train medical students for real world applications of their knowledge and skills. The ability of health-care providers to react sensibly in an unexpected situation is not a skill that a person is born with, but rather acquired by training and practice which is developed over time. Advances in technology have created new and better methods for training medical students. One of the most exciting innovations in health care is in the field of medical simulations, which is aimed at reducing medical errors, improving patient safety and reducing overall health-care costs. Simulation technologies offer exciting possibilities for skill evaluation and clinical practice improvement.

Currently, simulations are being used in education and training to enhance understanding, feasibility and reliability, to improve performance and to assess competence. It protects the actual patient from procedures being performed by inexperienced trainees. Computer-aided diagnosis is often used to educate clinical practitioners and medical students for reducing hospital errors. "*A framework for the analysis of acoustical cardiac signals*" by Zeeshan Syed [10] proposed a framework and associated software to primary care physicians to teach cardiac auscultation using presentation tools for computer assisted diagnosis of cardiac disorders [10]. A sequence of steps is being followed by the cardiologists or medical students to perform cardiac auscultation which includes irrelevant beats, selectively tuning into particular frequencies and aggregating information across time to make a diagnosis. Through the use of digital

signal processing, the information is enhanced and the medical students can hear the sounds more clearly, and the visual prototypical beat highlights the timing and shape of the murmurs [10]. The disadvantages of using certain simulators are that the users do not interact with a live person and do not acquire all the clinical skills. This is very different from human interactions where the medical students are not prone to factors of clinical training. In our research we use standardized patients to improve the clinical skills of the medical students by directly interacting with the person, and hence, hone their communication skills.

The solution for the problem mentioned above is in combining augmented reality technology with SP's to improve the level of medical training and the ability of the SP to simulate abnormal physical findings. "*Augmented Standardized Patients Now Virtually a Reality*" by Frederic D. McKenzie [2] suggested the importance of augmented SP's which would expand the opportunity for medical students, to learn more clinical skills in a realistic setting with a real person (SP) in the areas of medical decision-making, eliciting the history, doctor-patient communication skills and physical examination [2]. Augmented SP's can elucidate more abnormal conditions than a normal SP or the traditional patient-based training, thus it is considered as a valuable teaching tool for the medical students and clinical practitioners.

The Master's thesis by Reneyl Castelino [5] on "*Augmented Reality for Auscultation in Standardized Patients*" describes a technique that uses magnetic sensors on the head of the electronic stethoscope to augment cardiac and pulmonary sounds on the SP [5]. After tracking the location of the stethoscope, two distinct sounds, one of which is recorded from the real patient and the other retrieved from the archived database

of sounds on a computer by matching its tempo are being triggered by an SP and the medical student can hear the sound to diagnose the patient. The sound being played is changed as the stethoscope is moved over different areas of the SP. Twenty-six heart and lung sound locations were augmented and these locations were characterized as hot zones [5]. Even though this research is an efficient way of tracking the EKG signal, it is very costly due to the use of magnetic sensors for tracking heart EKG signals. This problem is overcome in our research by considering the electrical activities of the heart for tracking the different areas of the heart EKG signal.

There is a lot of research carried out on the transmission of the EKG signal for the quick diagnosis of patients. "*Real Time Analysis and Diagnosis of Tachycardia Condition from Electrocardiogram (EKG) Data,*" by P.O. Bobbie [16] designed an algorithm for analyzing and detecting cardiac conditions of the most common types of cardiac abnormalities [16]. It is achieved by capturing the EKG data and analyzing the P-wave, QRS complex and T-wave in the EKG signals. The advantage of this project is that it provides an affordable and portable solution for EKG signal analysis for the remote monitoring of cardiac patients. The main drawback of the system is its incompatibility to use in finding other heart abnormalities and also noise due to the transmission of the signal to the remote location. This research was initially used to build the circuit for recording the EKG signals at the various areas of the heart, but due to the constraint of using medically approved stethoscopes for the research and limited options of saving the recorded files, use of electronic stethoscope was necessary.

There is not much research in the detection and alignment of the QRS complexes, which can be considered as the most important part of our research. Pablo Gomez [4]

proposed an algorithm to process the EKG signals for the detection and alignment of the QRS complexes, to compute the average RR interval and the cardiac rhythm, and to plot the graphs for QRS complexes [4]. The heart abnormalities are found by the variations in the cardiac rhythm and hence all the variations in the heart signals are not recognized using this technique. The algorithm is being used for the processing of the EKG signal and the detection of the QRS complexes. An effective time domain method of QRS complex detection is using a consecutive monotonically increasing point's algorithm which is implemented to reduce the processing time. The frequency filtering removes the noise as well as the components of the signal of interest at the same frequency of the noise [4]. In the algorithm, QRS with the shortest duration is selected as a template to find the rest of the QRS complexes. The template is correlated 21 times with the input signal and the QRS complex is admitted if the correlation factor is greater than 0.5 or else it is rejected. This algorithm is applicable only for positive peaks and hence needs improvisation for negative peaks. Along with the duration of the signal which was the only parameter in the above algorithm, our algorithm was improvised to find the peak of each QRS for both positive and negative peaks. This was later used as parameters for classification.

Most of the related research is concentrated on processing the heart sounds for abnormalities. "*Automated Pediatric Cardiac Auscultation*" by Jacques Pinard De Vos [3], designed an automated algorithm to assist the physicians in classifying the heart sounds into normal and pathological classes and improving the decision-making capability of the clinical practitioner by not referring to the cardiologist if abnormal murmurs are found [3]. The heart sounds are processed to filter out the noise artifacts and

are classified using three feature extraction algorithms namely direct ratio, wavelet method and neural networks. The direct ratio method extracts the time dependent energy content to serve as an indicator of pathology and a wavelet processing method uses the time frequency analysis technique to represent the heart sound frequency dynamics without creating cross-term artifacts [3]. A neural networks classifier is used as a pathology classifier to test the above discussed method's performance and certain improvements are made [3]. The model is inefficient for all the types of murmurs and is applicable only to systolic murmurs. The main disadvantage of this model is due to the misclassification of the normal cases due to the large energy content in the early or mid-systolic region, an insufficient S1 sound and an irregular heart rhythm. The algorithm is valid only if the correlation between specific murmur types are the same for different patients with the same condition and only for a certain amount of murmur types [3]. Jacques Pinard De Vos [3] research concentrates on the sound signal, which may be an interesting addition to the future work in this thesis. In our research, A KNN classifier is used with duration and peak signals as parameters to classify the four main areas efficiently.

Hence, there is a need for more advanced techniques of tracking, detection and classification of the QRS complexes in an EKG signal for clinical training of medical students for the diagnosis of the patients.

CHAPTER 4

METHODS

4.1 Introduction

This research concentrates on acquiring the electrical signals from four areas of the heart, namely mitral, tricuspid, pulmonic and aortic areas as well as processing the acquired signals and comparing them. The signals are classified in later stages based on the duration and the peak of the individual QRS complexes. The intent is to use these models within a tracking capability for standardized patients, reducing the cost of using more expensive tracking methods such as magnetic sensing.

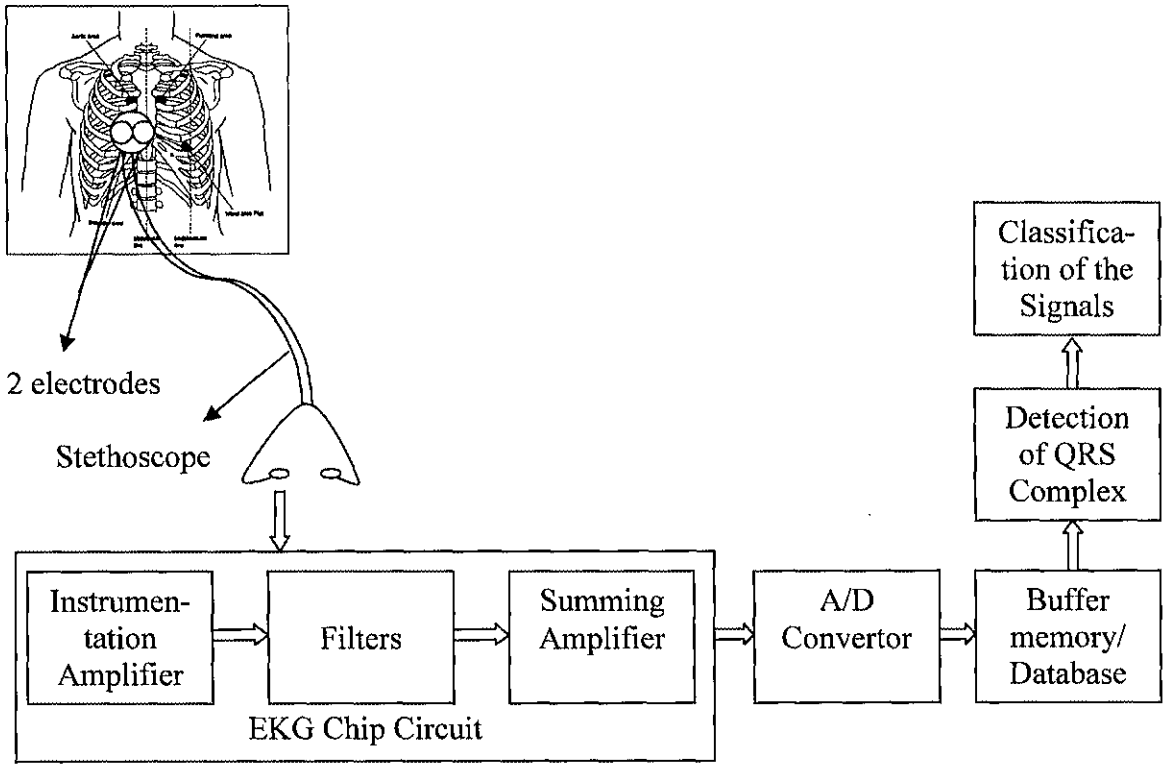

Figure 4.1: Ideal system diagram.

The ideal system diagram used for tracking the EKG signal is as shown above in figure 4.1. The EKG signal is recorded from the four main areas with the 2 lead moving EKG reusable electrodes kept close to each other. The type of electrodes and the electrode gel that is used in this research is discussed in the further sections.

The EKG chip circuit is discussed in detail in Chapter 2. It has an instrumental amplifier at the front end to amplify the low amplitude EKG signal, followed by two filters- low pass and notch filter to remove the noise content in the signal. This is then passed through a summing amplifier to make all the amplitude values positive in order to pass it through A/D convertor which can only take positive values. Analog devices ADUC831 data acquisition system which has a 12-bit ADC was used for digitization of the EKG signal. The bread board EKG chip circuit is shown in figure 4.2. The output signal is then saved in a database or buffer memory. The QRS complexes of the EKG signals are detected and classified which are discussed in the further sections.

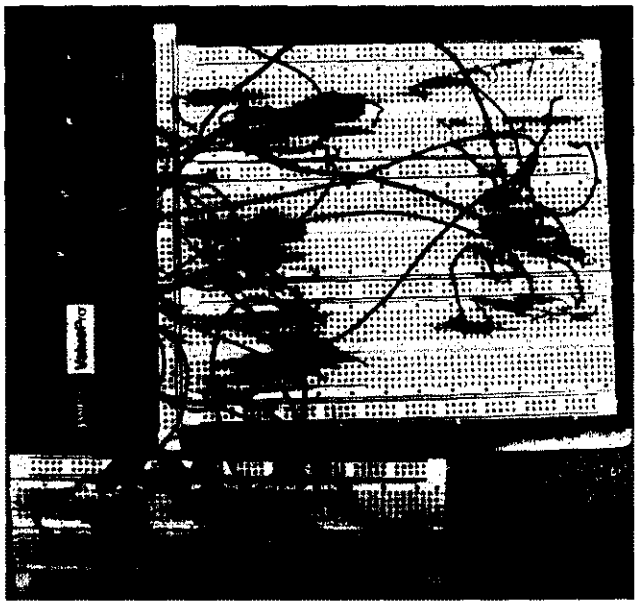

Figure 4.2: EKG chip circuit.

The initial idea for recording the EKG signal was to design an EKG circuit and monitor the saved recordings. The circuit design is discussed in detail, with all the schematics of each stage explained in previous sections. Signals from an EKG chip were also used to determine real-time capabilities. After the design and implementation of the EKG circuit was done, the usage of medically-approved EKG signal recording equipment was replaced due to the ease of use and stability for better signal acquisition. The Welch-Allyn stethoscope along with the Meditron analyzer was used which also had a facility to store the signals. This modified method is shown in figure 4.3. Here, the two electrodes are connected to the Meditron analyzer which in turn is connected to the computer to record the signals and then save it for further processing. Each stage is discussed in further sections.

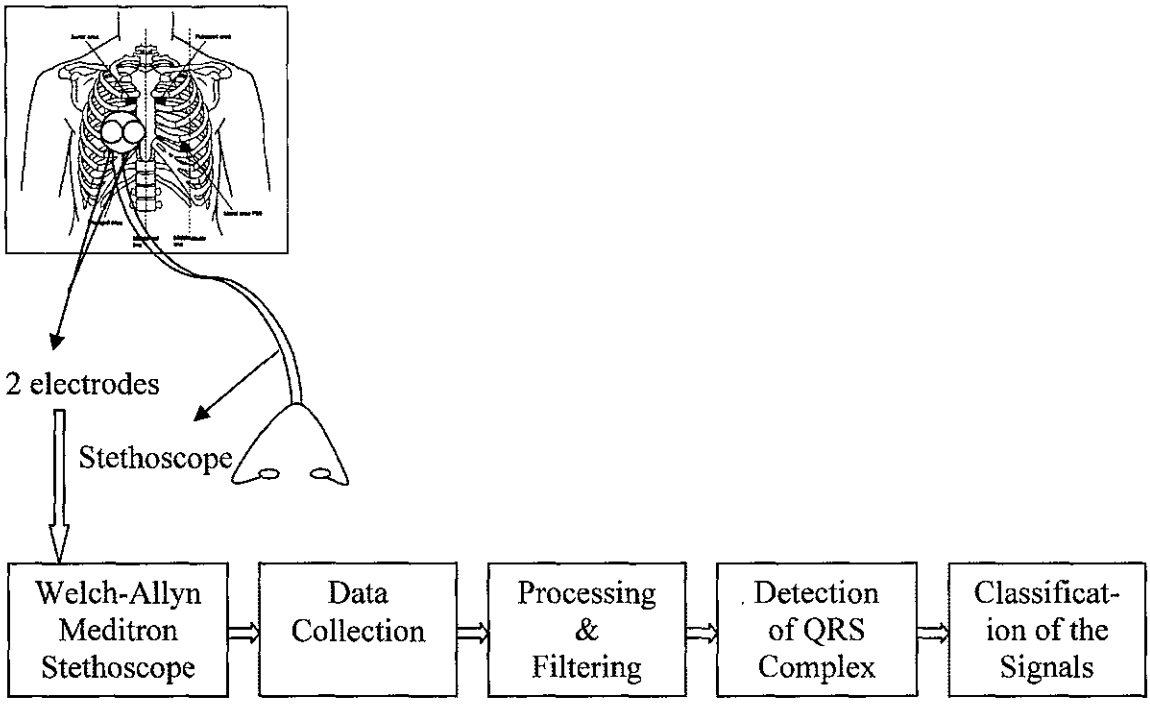

Figure 4.3: Modified system diagram.

4.2 Electrodes

Generally, electrodes are direct contact types which are used for sensing bio-electric potentials caused by muscle and nerve cells. The 2 lead moving EKG reusable electrodes were applied to the subject's chest for recording the EKG signal. If the iso-electric line was unstable, the electrodes would be repositioned until a relatively stable iso-electric line was obtained. All the recordings were done with the subject in sitting position to avoid any disturbance or movement in the electrodes. If the recordings are not good enough or too noisy then it is discarded to avoid the errors during classification. An electrode gel is also being used to reduce the noise.

4.3 Welch-Allyn Meditron Stethoscope and Data Collection

Electronic stethoscopes are used in research to overcome low sound levels by amplifying body sounds. The acoustic sound waves are converted into electrical signals which are then filtered, amplified and processed. The leading suppliers of the electronic stethoscopes are Meditron (Welch-Allyn), 3M (Littmann), Cardionics and Thinklabs. There are different types of sensors used in the detection of the sound. Cardionics stethoscopes use microphones in the chest-piece but have their own disadvantages of noise interference and hence are seldom used these days. Welch-Allyn's Meditron stethoscope uses a piezoelectric crystal placed at the head of a metal shaft and the bottom of the shaft is connected to the diaphragm [7]. 3M also uses a piezoelectric crystal which is placed within the foam which is embedded behind a thick rubber-like diaphragm. Thinklabs uses a stethoscope diaphragm with an electrically conductive inner surface to form a capacitive sensor. Developments made in this field include noise filtering for the

electronic stethoscopes. Electronic stethoscopes are also being widely used for storing the waveforms on a computer and analyzing the recorded sounds of the signals.

Figure 4.4: Welch-Allen electronic stethoscope and Meditron analyzer.

The data used in this research is recorded using a Welch-Allyn Meditron stethoscope which is connected to a computer via Meditron analyzer. The Welch & Allen Meditron analyzer shown in figure 4.4 uses a new sensor technology, piezoelectric crystal to record the sound waves and the electrical signals of the heart that are retrieved from the two leads connected to the Meditron analyzer. Hence it can be used as sound recordings, patient documentation, interactive teaching of students and analysis of the Phonocardiogram and EKG signals. The sensor is small and is centered in the white circular region of the chest piece. It is highly directional and sensitive. The use of an electrode gel on the patient's area of auscultation reduces the noise and the disturbing scratching caused due to hair in the auscultation area. The phonocardiograph is an instrument used for recording the sounds connected with the pumping action of the heart. These sounds provide an indication of the heart rate and its rhythm.

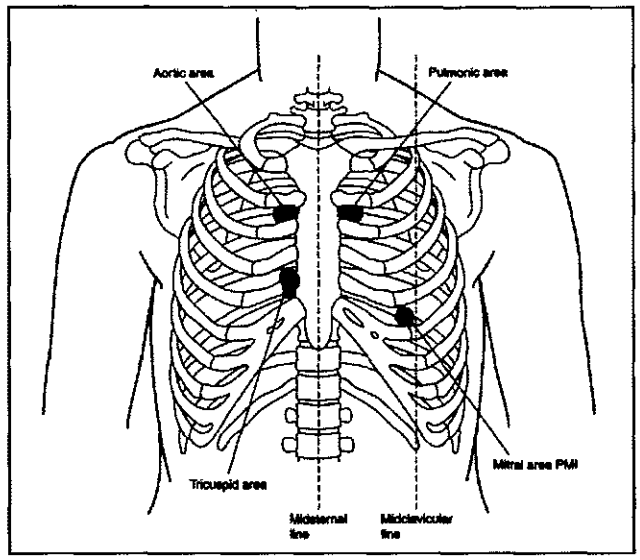

Figure 4.5: Cardiac auscultation areas [17].

The Meditron analyzer allows recording, listening and storing the patient's phonocardiogram and EKG signals in the database for further processing and analysis of the signal. The patient information can also be given which makes it easier for analyzing individual patients and accessing the files. The EKG signal, being the signal of interest, is actually recorded at various areas of the heart namely the mitral, tricuspid, pulmonic and aortic area by the two leads kept close to each other. The four main areas are as shown in figure 4.5.

The digital recordings are stored without pre-filtering and hence an excessive sampling frequency of 44.1 KHz was used to filter the noise and to avoid aliasing. The optimal heart and lung sounds frequency setting in which the stethoscope operates are the 20-420 Hz and 350-1900Hz respectively. The heart frequency range was used for recording the EKG signals because we are not considering the sound signals. The heart sound and EKG signal were recorded on separate channels using a sampling frequency of 44100Hz per channel, with 16 bit resolution. The data was sent to the computer via a USB connection which is collected in the database and stored in separate files as a wave

file (.wav). These wave files can be accessed and the changes can be made if required. Optional notes are included like the point of the recording and patient position, which can be saved for future references. The subject information and the location of the recording are noted for easy access to the files. The most important thing to be observed during recording is that the stethoscope is not been used to record the sound signals rather only EKG leads is been used for recording the EKG signal. The sound recordings, stored in the database, is being passed through a 800 Hz low pass filter (LPF) that is a part of Welch & Allen recording equipment after which it was normalized with respect to the maximum amplitude equal to 0.8.

A total of 25 signals were recorded from the four main areas of the heart corresponding to 7 signals from the aortic area, 6 signals from the mitral area, 6 signals from the pulmonic area and 6 signals from the tricuspid area. These signals are recorded using 2 leads kept at equal distance during all recordings to avoid any errors.

4.4 Reading the input data in the MATLAB

MATLAB is a programming language which stands for matrix laboratories and is a product of The Mathworks. It is being used in various fields of research such as digital image processing, statistics, digital signal processing, machine learning, system analysis and medical imaging for plotting the data and functions, user interfaces, image processing, signal processing, classifications, algorithm implementation and fast computations. The data consists of around 10 to 11 seconds of EKG information which is stored in the data file as a wave format and is initially calibrated to a sampling frequency of 44100 Hz. The data which is collected is read by MATLAB using the *wavread*

function, which gives the main information about the EKG signal such as sample data (y), sample rate (Fs), number of bits per sample (nbits). This sampled data is plotted and analyzed for detection of the QRS signal.

4.5 Processing or filtering of the EKG signal

The main sources of noise are power line noise, poor electrode contact noise, motion artifacts, muscle contraction noise, respiration, electromagnetic interface from other electronic devices and noise coupled from other electronic devices, usually at high frequencies. Power line noise consists of interference in the EKG by the 60 Hz pickup and harmonics from the nearby AC power supplies. Poor electrode contact is due to the loss of contact between the electrode and the skin which causes a baseline drift. Motion artifacts are caused due to the shift in the baseline with the changes in electrode skin impedance. Muscle contraction noise is caused by the contraction of other muscles besides heart and Respiration noise is due to the drift in the base line. It is important to filter these noises for the accurate detection of the EKG signal.

During the removal of noise, utmost care must be taken to ensure that the noise removal technique does not affect the information bearing data. A low pass filter is used to remove or filter the noise above 800Hz. Since only two leads are being used to record the EKG signal instead of using the stethoscope to record the sound signal, these noises do not have considerable affect on the EKG signal. The ambient and electrical noises can be reduced by initially calibrating the stethoscope and using correct recording techniques. The noise due to movement artifacts can be minimized by correct placement of electrodes, quiet recording environment and a good firmly pressed secure recording. The

use of electrode gel while recording the EKG signal reduces the noise originating from friction due to the skin contact and results in a recording of better quality.

The digital filter was implemented after the input EKG signal is being read into the MATLAB to remove any baseline drift which influences the detection of the QRS complexes. The maximum duration of the QRS complex is about 0.12 seconds which corresponds to 8.33 Hz in frequency domain. The filter has to be designed such a way that it has to filter out the baseline drift without any loss in the data above 8.33 Hz. The output signals contain the frequencies of up to 1200Hz. The frequency band of heart signals are 20 to 800 Hz, but the average maximum frequency band of the normal noise free heart signal is in the range of 20 to 650 Hz. In order to achieve this frequency range a low pass Butterworth filter of order 5 is designed and implemented with MATLAB filter toolbox, which has a sampling frequency of 44100 Hz and a fixed cutoff frequency of 23 Hz. The variations in the cutoff frequency provide a better output and much reduced noise in the EKG signal.

4.6 Detection of the QRS Complex

The following section discusses in detail the procedure for the signal's detection and alignment.

4.6.1 Initial QRS localization and determination of average beat

The most important process after the filtering of the EKG signal is detection and separation of the QRS complex. We have implemented an algorithm for detection and aligning of QRS complexes using a research paper by Pablo Gomez [4], on "EKG Signal Processing: An Algorithm to detect and align QRS Complexes," which separates each

QRS complex and computes the values of RRavg (average R-R interval in seconds), RRdev (standard deviation of R-R interval in seconds) and RRppm (cardiac rhythm in pulses per minute) for the positive peak QRS complexes [4]. The original algorithm is modified for detecting both positive and negative QRS complexes for the sampling frequency of 44100 Hz. The algorithm is also modified to find the peak of each QRS complexes in the signal which is used as a parameter for classifying the signals. The average QRS complex and the separated QRS complexes are plotted.

The modified algorithm flow for processing the EKG signal and the detection of the QRS complexes is as follows.

- Filter the input signal using a Butterworth Low-Pass filter of the order 5 and cut of frequency 23 Hz.
- Smooth the filtered signal using a 500 points average that includes the point itself and its 499 neighbors.
- The algorithm works in 2 modes, the QRS onset mode which denotes the start of the QRS complex and the QRS offset mode which denotes the end of the QRS complex.
- Start to find onset mode and locate 882 consecutive monotonically increasing points or decreasing points depending on the positive or negative peak QRS complexes (882 points is equivalent to 20ms).
- When the point is found, the prospect onset is located at the point equivalent to current point – 882. The value at the onset point is saved. Switch to find offset mode.

- To find offset mode, the threshold, defined as 32% of the peak of the signal, has to be reached within the next 1838 points (41ms). If the threshold is not found, it indicates the detection of a false QRS onset and hence has to switch back to find onset mode.
- If the threshold is reached, the search continues until the value of the signal falls below the value found at the onset point. This point is saved as the QRS offset and the mode is switched to find onset.
- To find the peak of each QRS complex, the point at which there is a steady decrease or increase above 50% of the signal's peak is noted for a positive peak and negative peak respectively.
- Once all the potential QRS complexes are found, their onset and offset values are stored in a QRS matrix. This is followed by the alignment in time using correlation.
- The QRS with the shortest duration is selected as a template to find the rest of the QRS complexes. It is defined as vector of 26460 points (600ms) with the QRS onset located at point 9261 (35% of 600ms).
- The template is correlated 21 times with the input signal. The reference point is the QRS onset. The correlation point begins at the onset point – 10 and ends at the onset point + 10. The maximum correlation factor is compared against 0.5. If it is greater than or equal to 0.5 (50%), the QRS is admitted, otherwise it is rejected. The value of 50% was chosen after analyzing the signals. The duration and amplitude of the QRS complexes vary so much that a 50% will be necessary to detect all legitimate QRS complexes.

- Each individual admitted QRS complexes are aligned and plotted.
- The Average Beat is obtained by adding all the admitted QRS complexes and dividing the result by the number of admitted QRS complexes.
- The R-R intervals are computed by calculating the difference between consecutive QRS onsets. The RR average intervals in milliseconds, standard deviations and the cardiac rhythm in pulses per minute are calculated.

The algorithm is also represented in the form of a flow chart which emphasizes on the main functions used in the MATLAB coding.

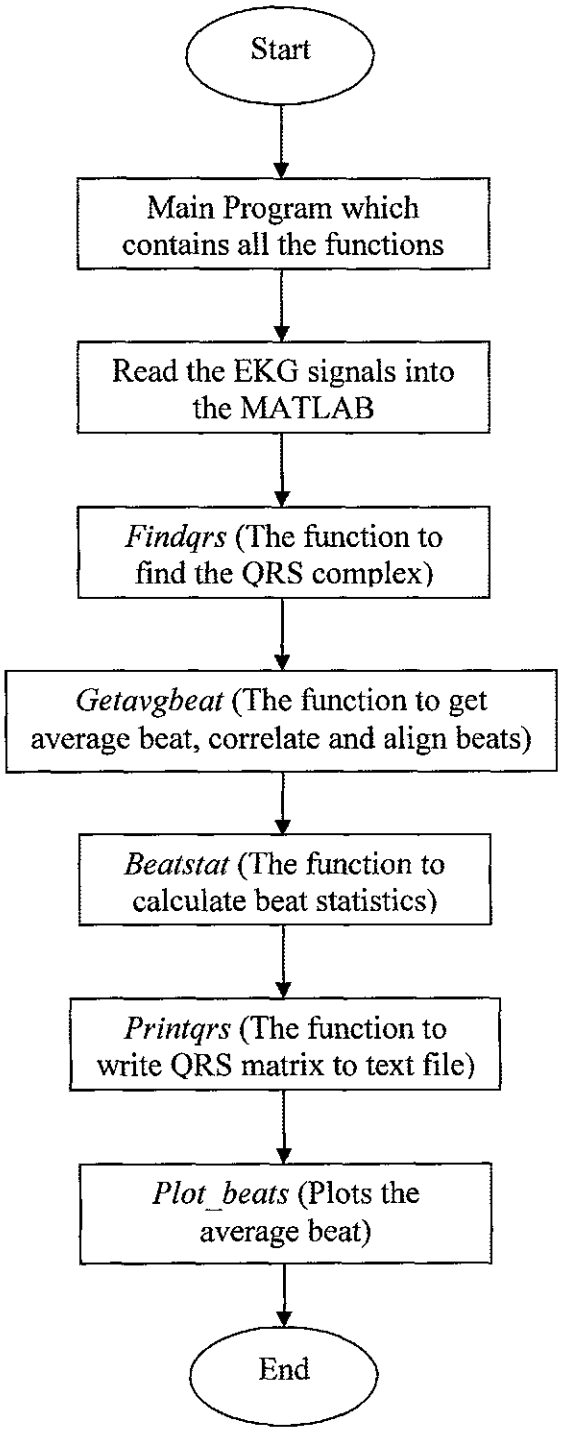

Figure 4.6: The MATLAB implementation of the technique.

To determine an effective time domain method of detection of QRS complexes, the input EKG signal is filtered for noise removal and motion artifacts using a frequency filter Butterworth low pass filter and is further smoothened using a 500 points average by reducing the processing time. The algorithm works in the two modes of operation and forms the basis for detection of all the prospective QRS complexes by using consecutive monotonically increasing or decreasing points depending on whether they are positive or negative QRS peaks. Once all the prospect QRS complexes are found and their onset and offset values are stored in a QRS matrix, the alignment in time using correlation begins. The shortest QRS duration is considered as a template to correlate and align the other heart beats. Get the summation of squares of the template points (sum_temp1). The template is correlated 21 times with input signal. It is first aligned to start from a specific point which is the onset of the current QRS detection and the correlation point begins at the onset-10 and ends at the inset +10. Correlate the template with all the QRS complexes found. The maximum correlation point is then found and replaced in the place of onset of the current QRS so that all the beats start at the same point and there is a localization of all the QRS complexes. The correlation factor for each of the QRS complexes is found by the ratio of the maximum correlation value and square root of the product of summation of the squares of the template point and EKG points in the template window. The QRS is admitted if the correlation factor is greater than or equal to 0.5, otherwise it is rejected.

The average QRS or beat is obtained by adding the admitted QRS complexes and dividing the result by the number of them which are then plotted using the MATLAB function *getavgbeat* function. MATLAB code was written to verify the algorithm by plotting all the detected and aligned QRS complexes in the EKG signal separately. The

duration of each QRS complexes, being the most important parameter, is found by subtracting the offset and onset values. The peak value of each QRS complexes is also found as a second parameter to classify the signals. This is also stored to aid in the classification of the QRS complexes. Another function is implemented for recording the RR average interval, standard deviations and the cardiac rhythm of the EKG signal.

4.5.2 QRS Identification using an average template

The same process explained in the section 4.5.1 is repeated with an additional step in the algorithm which includes the average beat obtained in the section 4.5.1 as a template to correlate and align the QRS complexes. The task is achieved by calling the *getavgbeat* function twice in the main MATLAB program, the first time for using the shortest duration QRS complex to obtain the average beat and the second time to use the average beat obtained from the first stage to correlate and align the QRS complexes. The main advantage of using the average template is all the QRS complexes will have higher correlation factors, which increases the possibility of identifying accurate QRS complexes by taking into consideration the correlation and average beats.

4.7 Classification of the signals

Firstly, all the signals are classified into four major signals according to the position of the stethoscope in the four major areas of the body. Then the concept of 5-fold cross validation is used to classify the signals into testing data and training datasets randomly. The data set is divided into 5 subsets, and each time one of the 5 subsets is used as the test set, the other 4 subsets are put together to form a training set. The process

is repeated 5 times so that each subset is used for testing once. After the 5-fold cross validation, the 5 test results are pooled together to compute the accuracy of the testing data. K-nearest neighbors (KNN) classifier is used to classify the signals which the simplest of the machine learning algorithms.

The K-Nearest neighbor (KNN) classification algorithm tries to find the K nearest neighbors of the object and uses a majority vote to determine the class label of the object [18]. Here, K is a positive integer and is usually considered an odd number to avoid tied votes. For example if K=1, then the object is simply assigned to the class of its nearest neighbor. "The performance of K depends on the choice of K as well as the distance metric applied" [18]. The parameter K governs the degree of smoothing, so that a small value of K leads to a very noisy output whereas large values of K are more resistant to noise on the classification making the boundaries smooth between the classes. The value of K should be neither too large nor too small for optimal results [19]. This simple and easy to implement method can yield very competitive results compared to the most sophisticated machine-learning methods [18].

In this KNN classification algorithm, the K value is considered as 3 which are optimal for getting a high accuracy. The accuracy can be degraded due to noise or irrelevant features. The input parameters are the duration and peak of the each QRS complex. The class ID's are assigned from 1 to 4 for each of the four main areas namely aortic, mitral, pulmonic and tricuspid areas, respectively. The output accuracy is obtained and a set of data is applied on the classifier at the end to check if the signals are correctly classified. This even shows the class to which the data belongs.

CHAPTER 5

RESULTS

The EKG signals recorded from the four major areas using a Welch-Allyn Meditron analyzer is read into MATLAB using the wavread command and is plotted for further processing of the signal. The MATLAB code samplecode1.m (see appendix A) reads the input data and calls the various functions used in the detection of QRS complexes. The signals are vectors containing 466944 points sampled at 44100 Hz, which denotes approximately 10.588 seconds of EKG information in each signal. Since showing the results of all the signals is a tedious task, one each from all the four areas is being plotted for a better understanding. Figures 5.1 to 5.4 plotted below are the EKG signals at the four main areas with amplitudes in millivolts (mv) on the Y-axis and time in seconds (sec) on the X-axis. The figures to the right side show the zoom in snapshots of the EKG signal at various areas.

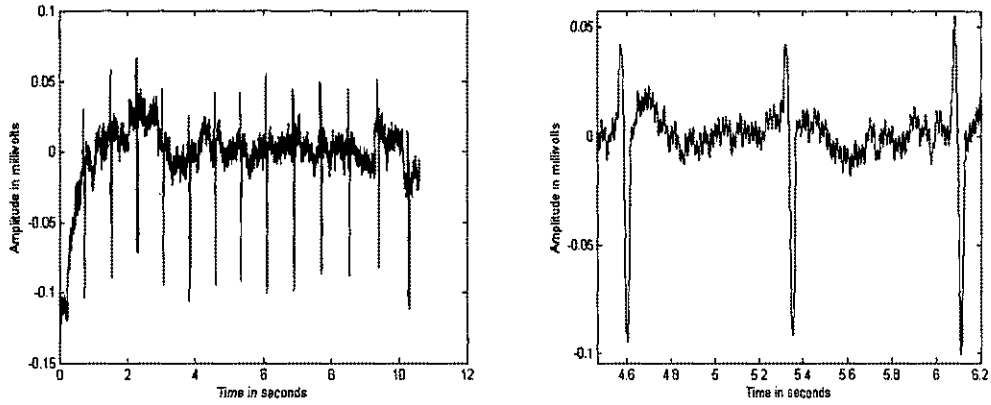

Figure 5.1: The EKG signal (left) and zoom in snapshot (right) recorded at aortic area.

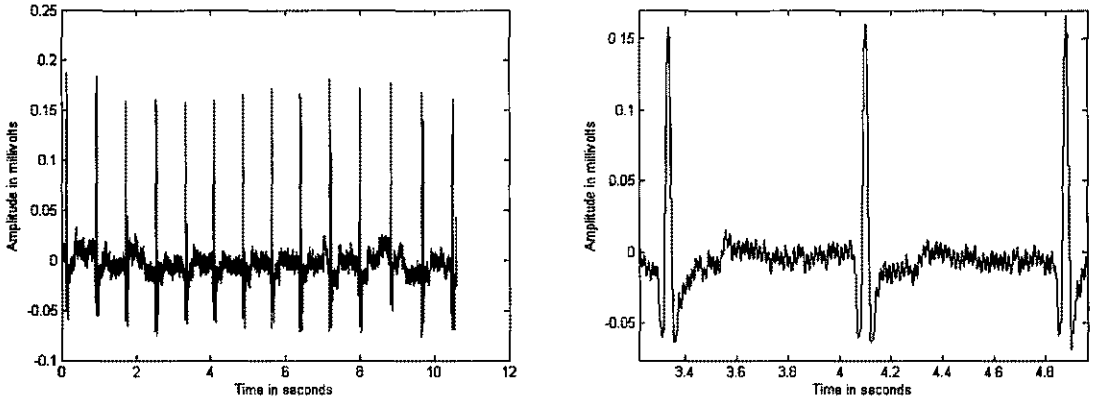

Figure 5.2: The EKG signal (left) and zoom in snapshot (right) recorded at mitral area.

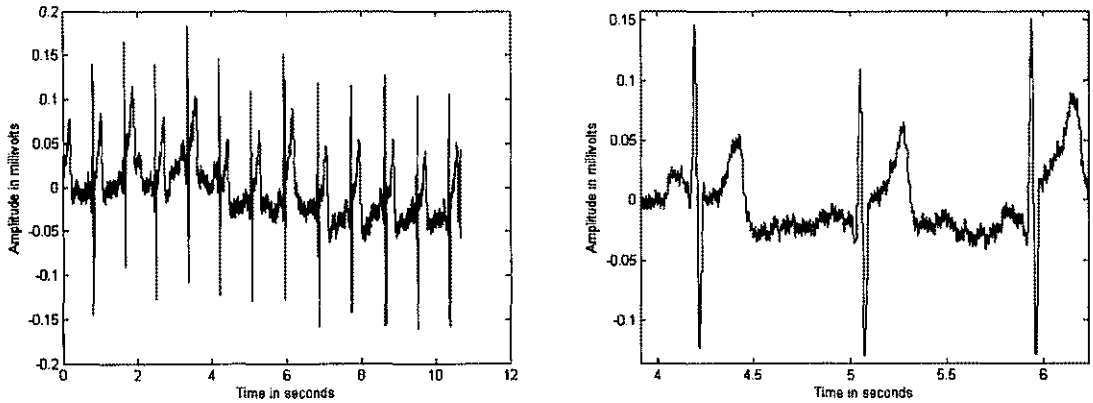

Figure 5.3: The EKG signal (left) and zoom in snapshot (right) recorded at pulmonic area.

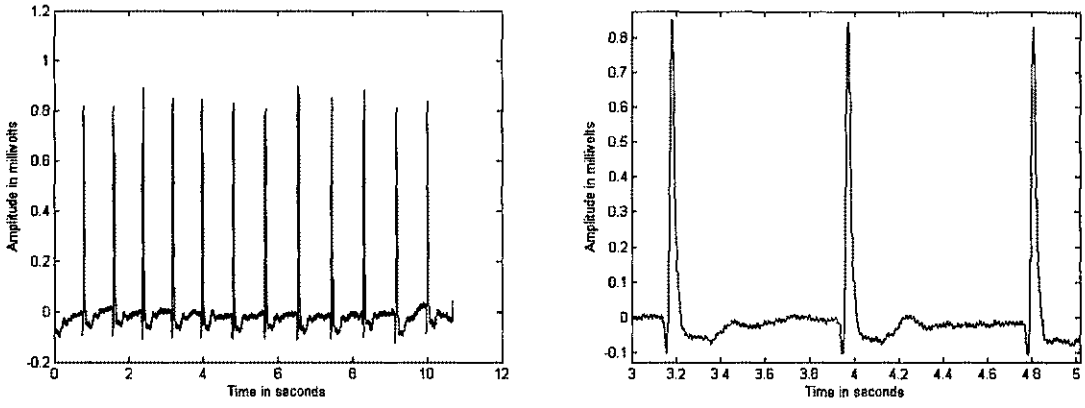

Figure 5.4: The EKG signal (left) and zoom in snapshot (right) recorded at tricuspid area.

These signals are then processed using a Butterworth low-pass filter and the outputs are plotted. The peak of each QRS wave is denoted by a cross mark ('x') which is used as one of the parameter for classifying the EKG signals in the later part. This is done by using the find_peak.m (see appendix A) MATLAB code.

The obtained output is then smoothened and then each QRS wave is separated out which is done using the MATLAB code findqrs.m (see appendix A). The signal after filtering and smoothening is plotted as shown in figures 5.5 to 5.8 below. The figures to the right side show the zoom in snapshots of the EKG signal at various areas.

From the outputs it clearly denotes that the noise has been removed. The snapshots of the EKG signals at the all the four main areas are zoomed in to show clearly the signal output and compare it with the separated QRS complexes.

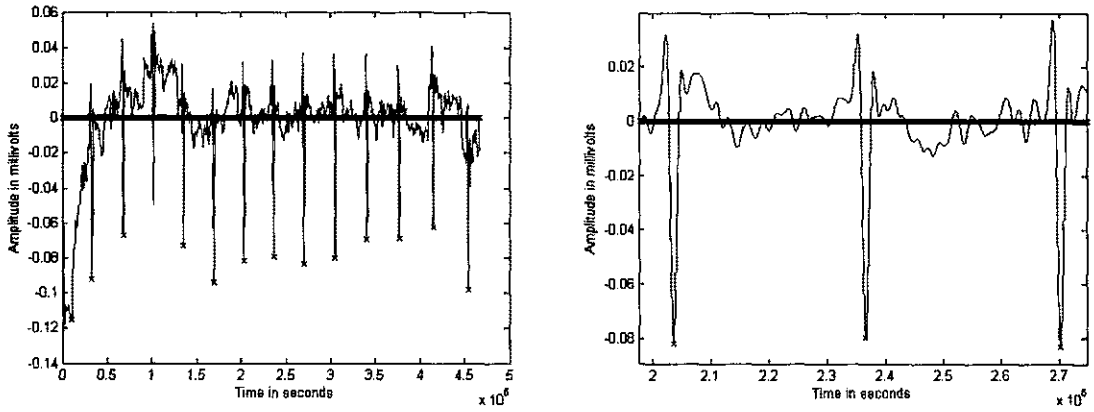

Figure 5.5: The filtered EKG signal (left) and zoom in snapshot (right) at aortic area with peak amplitudes.

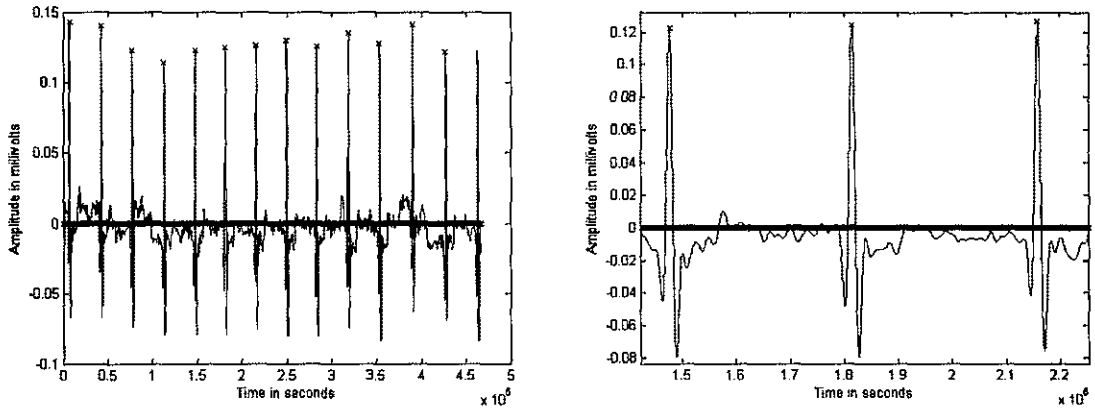

Figure 5.6: The filtered EKG signal (left) and zoom in snapshot (right) at mitral area with peak amplitudes.

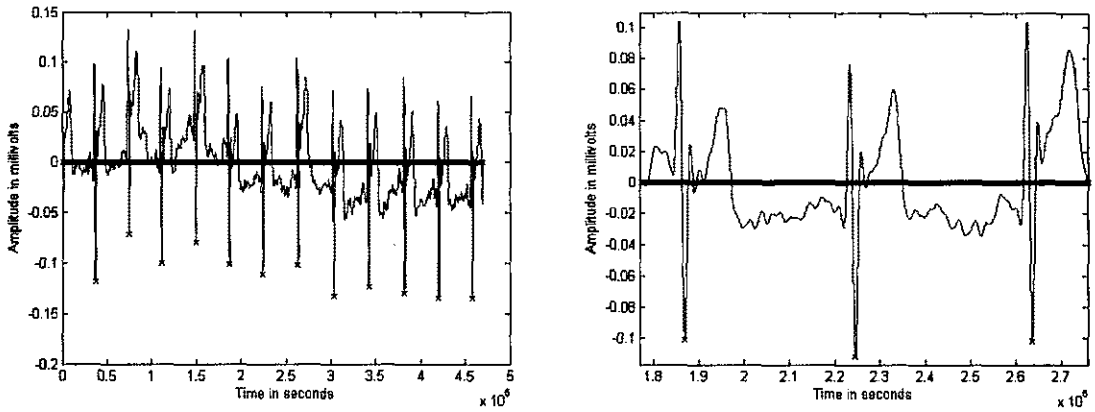

Figure 5.7: The filtered EKG signal (left) and zoom in snapshot (right) at pulmonic area with peak amplitudes.

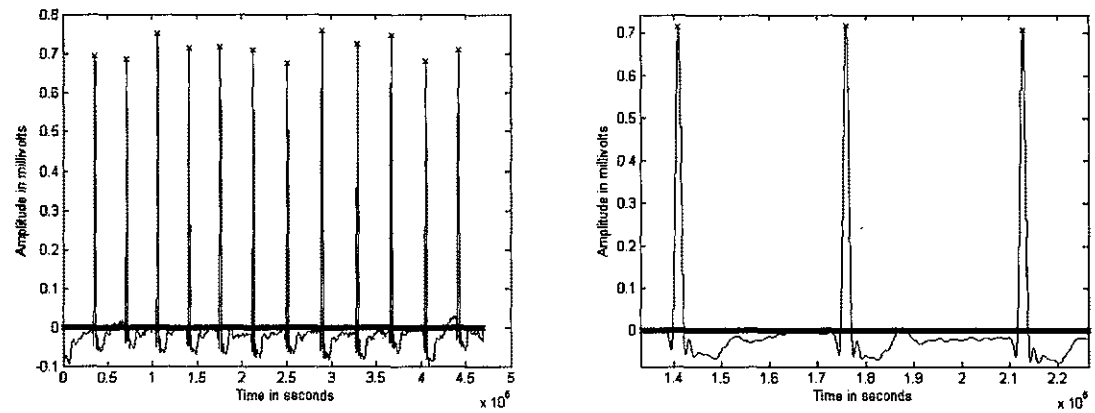

Figure 5.8: The filtered EKG signal (left) and zoom in snapshot (right) at tricuspid area with peak amplitudes.

A MATLAB code plot_beats.m (see appendix A) was written to verify that the algorithm can effectively locate and align all possible QRS complexes in signal. The following figures 5.8 to 5.12 shows the QRS complexes found for each EKG signal. These QRS complexes are aligned to get accurate results for finding the peak of the signal and to find the average beat of the signal.

The average beat of each EKG signal is plotted as shown in figures 5.13 to 5.16 below. The average beat is found by summation of all beats divided by the number of beats. From the outputs, it clearly denotes that the noise has been removed. The resulting average beat shows the PQRST signals. This part of the code is done in the function getavgbeat.m (see appendix A) MATLAB file.

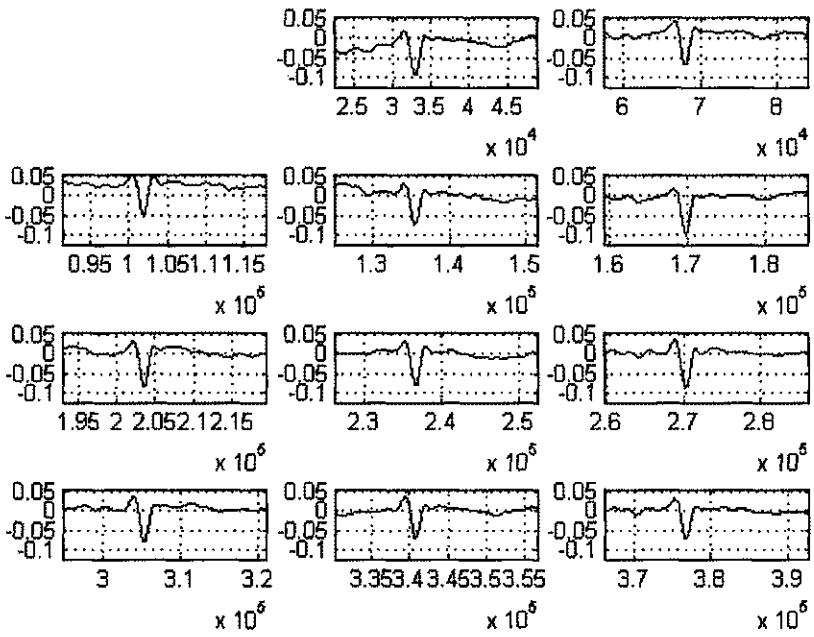

Figure 5.9: The beat 1 to 12 of 13 for EKG signal recorded at aortic area.

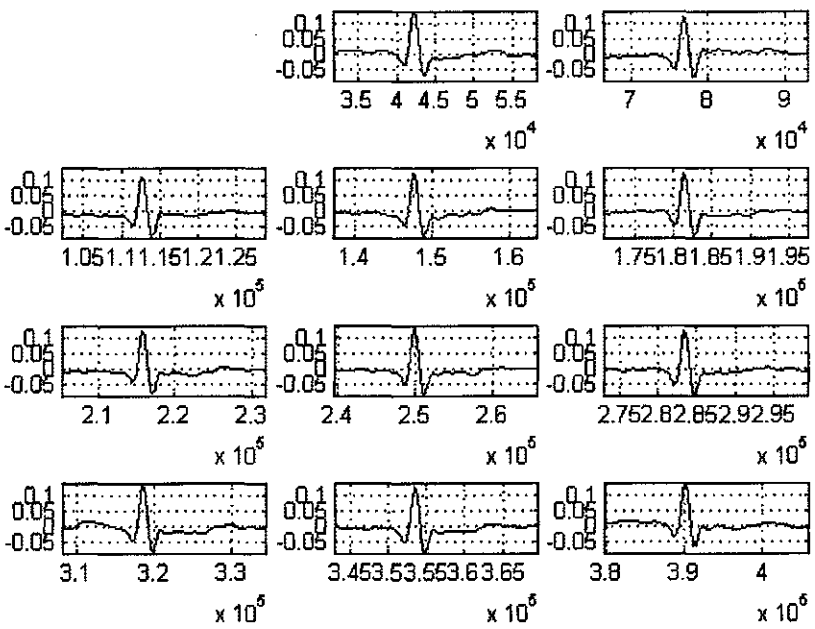

Figure 5.10: The beat 1 to 12 of 13 for EKG signal recorded at mitral area.

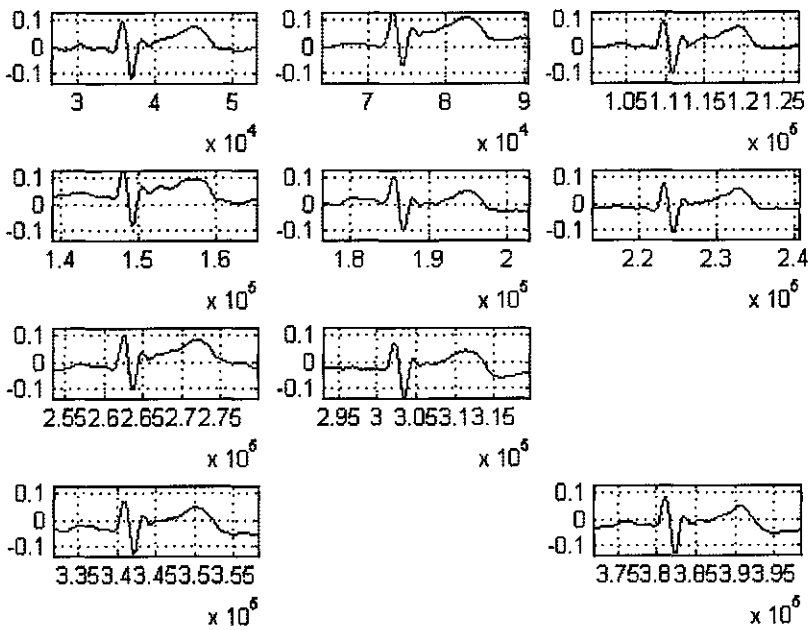

Figure 5.11: The beat 1 to 12 of 13 for EKG signal recorded at pulmonic area.

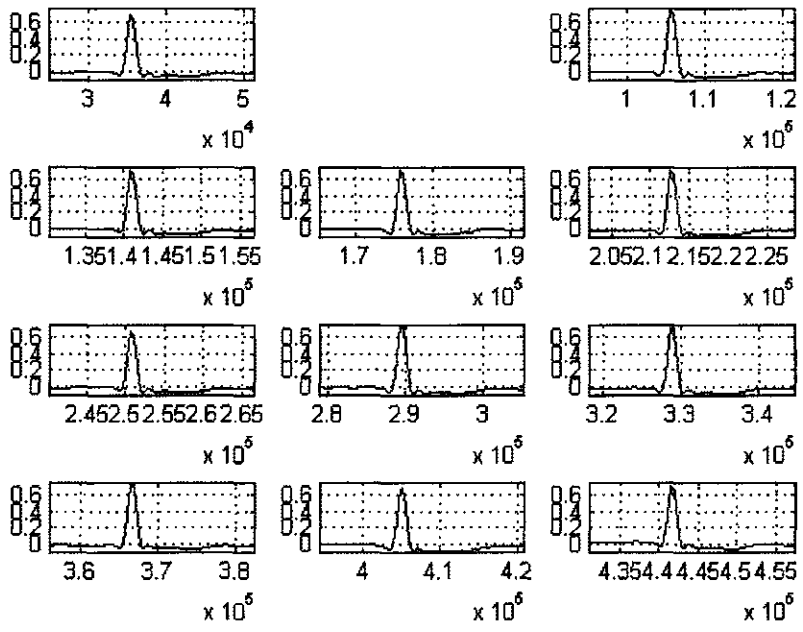

Figure 5.12: The beat 1 to 12 for EKG signal recorded at tricuspid area.

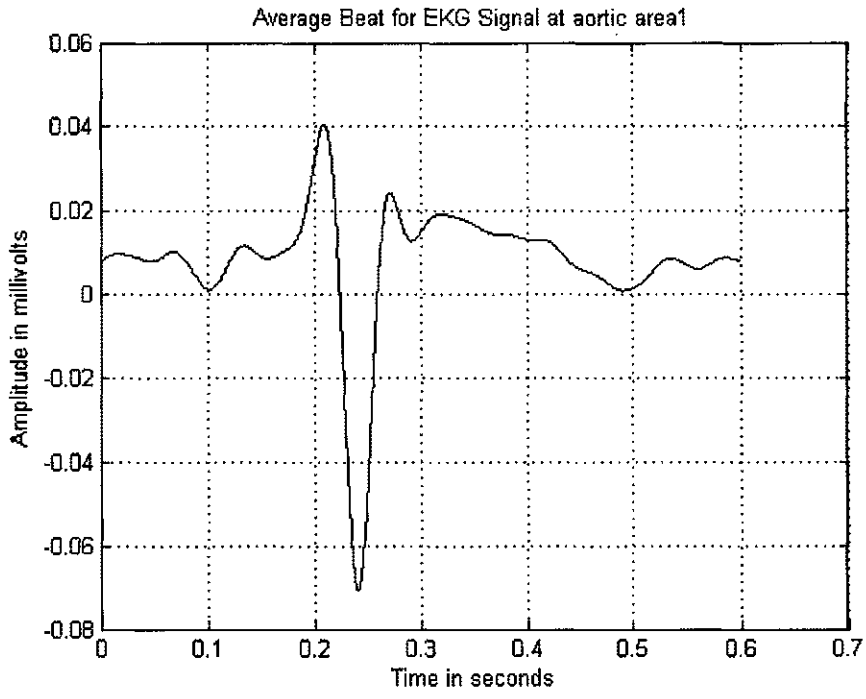

Figure 5.13: The Average beat for EKG signal recorded at aortic area.

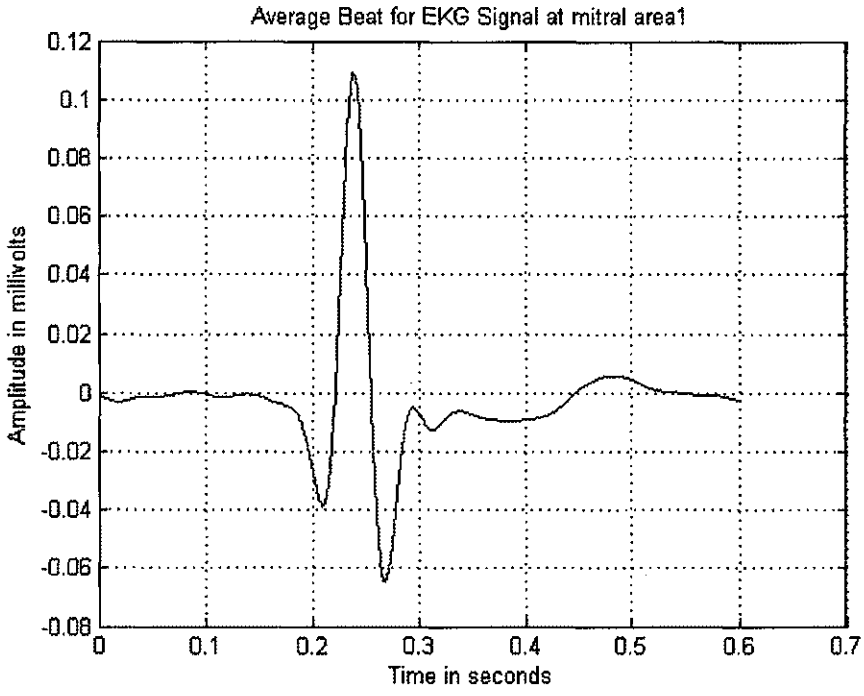

Figure 5.14: The Average beat for EKG signal recorded at mitral area.

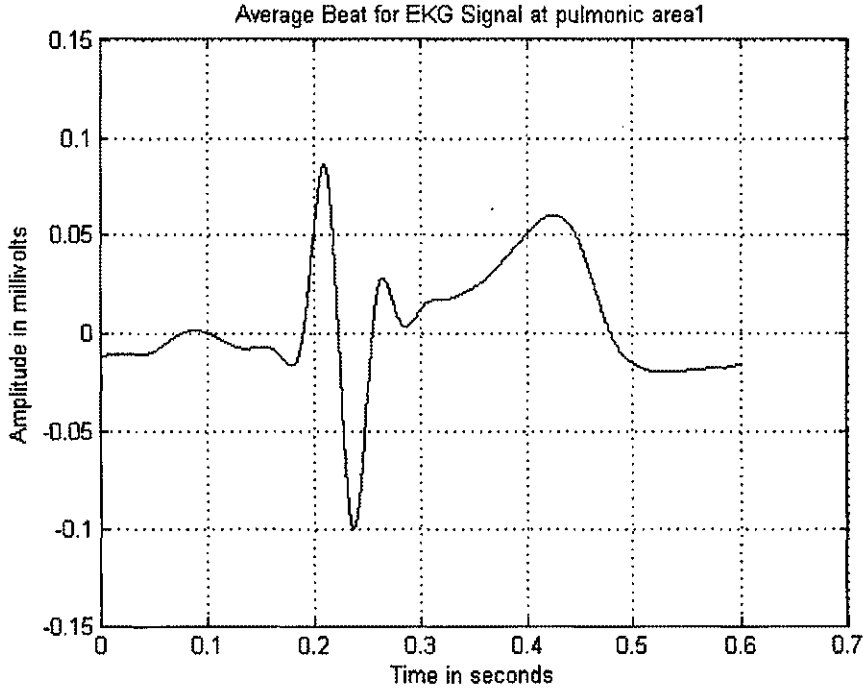

Figure 5.15: The Average beat for EKG signal recorded at pulmonic area.

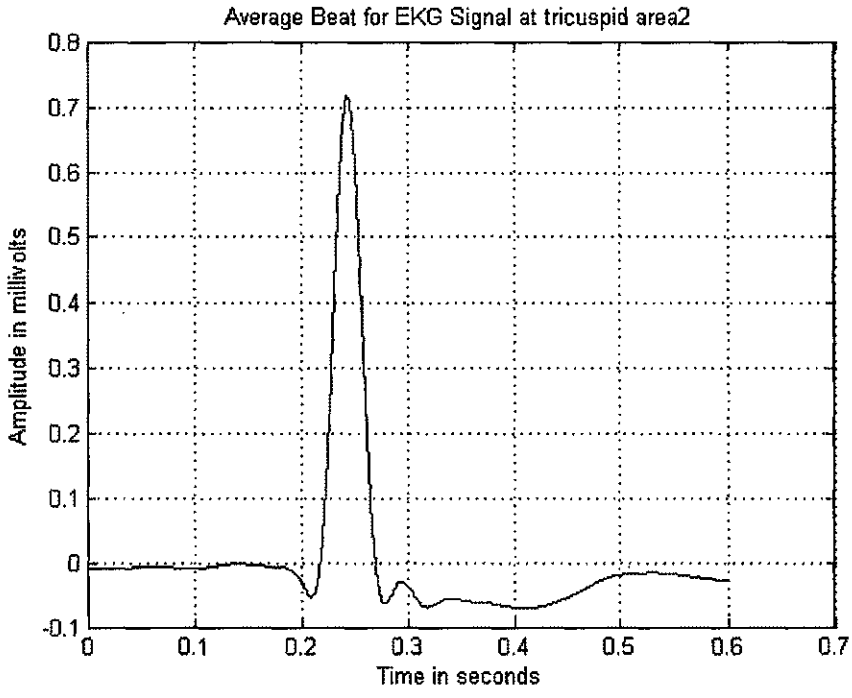

Figure 5.16: The Average beat for EKG signal recorded at tricuspid area.

The MATLAB code beatstat.m (see appendix A) prints out the RR average, RR deviation and RR beats per minute and the printqrs.m (see appendix A) code is used to print the onset, offset, peak amplitude and acceptance/rejection of each QRS complex of the signal into a separate file. The acceptance or rejection of the QRS complex is based on the correlation factor. If the correlation factor is greater than 0.5, then the QRS complex is accepted or else it is rejected. 1 denotes acceptance and 0 denotes rejection.

The tables shown below are just for EKG signals corresponding to each of the four main areas namely the aortic, mitral, pulmonic and the tricuspid areas respectively. The following tables 5.1 to 5.4 shows values for the signals obtained.

Table 5.1: Locations of onset and offset for EKG signal recorded at aortic area.

Onset	Offset	Peak amplitude	Admitted/Rejected
31605	34406	-0.1045986	0
66645	69349	-0.1034999	1
100561	103247	-0.1246916	1
134152	136864	-0.1159349	1
168388	171208	-0.0909847	1
202206	204949	-0.1049781	1
235267	237972	-0.1086124	1
268907	271617	-0.1048084	1
303881	306693	-0.09506868	1
339396	342088	-0.09453615	1
375415	378124	-0.08323847	1
413407	416129	-0.1309151	1

From the Table 5.1, we see a total of 12 QRS complex were detected, 11 were admitted and 1 of them was rejected.

Table 5.2: Locations of onset and offset for EKG signals recorded at mitral area.

Onset	Offset	Peak amplitude	Admitted/Rejected
5694	7873	0.1711959	1
40923	43188	0.1747112	1
75642	77847	0.1677241	1
111403	113578	0.159472	1
146363	148567	0.1670131	1
180141	182339	0.1723386	1
214549	216724	0.1673448	1
248592	250778	0.1771492	1
282184	284400	0.1774562	1
317258	319478	0.1799459	1
352225	354471	0.1778793	1
388830	391041	0.1729494	1
425893	428223	0.1761888	1
461704	463913	0.05226611	1

From the Table 5.2, we see a total of 14 QRS complexes were detected and all of them were admitted since the correlation factor is greater than 0.5.

Table 5.3: Locations of onset and offset for EKG signal recorded at pulmonic area.

Onset	Offset	Peak amplitude	Admitted/Rejected
35727	38182	-0.183463	1
73234	75719	-0.1729896	1
109720	112153	-0.1649151	1
147995	150454	-0.1805793	1
185554	188006	-0.1654542	1
223294	225765	-0.1594744	1
262490	264894	-0.1736694	1
302270	304759	-0.1740734	1
340992	343400	-0.1763296	1
381165	383581	-0.1847182	1
419255	421712	-0.03304671	1
456930	459389	-0.03646773	1

From the Table 5.3, we see a total of 12 QRS complexes were detected and all of them were admitted since the correlation factor is greater than 0.5.

Table 5.4: Locations of onset and offset for EKG signal recorded at tricuspid area.

Onset	Offset	Peak amplitude	Admitted/Rejected
34118	36990	0.7435281	1
104336	107216	0.8030744	1
139485	142345	0.7609979	1
174432	177344	0.7738769	1
211267	214129	0.7698572	1
249266	252100	0.7290639	1
288029	290869	0.8179673	1
327459	330317	0.7885249	1
365185	368090	0.7889691	1
403576	406381	0.7451371	1
440144	443012	0.7418051	1

From the Table 5.4, we see a total of 11 QRS complexes were detected and all of them were admitted since the correlation factor is greater than 0.5.

The duration and peak of all QRS complexes are obtained and stored in a file 'ECG2lead.txt' which is used for classification. The MATLAB code classifytrial03new.m (see appendix A) is used to classify the EKG signal. The figure 5.17 shows the plot of the duration and peak of the QRS signal from the four main areas,

which corresponds to the parameters of classification. The colored dots correspond to each QRS complex and each color corresponds to one area of the heart. The colors red, green, blue and black correspond to aortic, mitral, pulmonic and tricuspid area respectively. After the 5- fold classification, the training and testing data set is obtained which is then applied to a KNN-classification. The result is plotted as shown in figure 5.18 and the accuracy is computed by the ratio of the error in classification and the total number of objects classified.

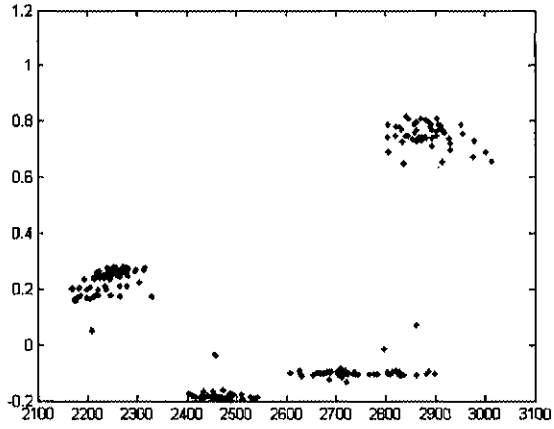

Figure 5.17: Plot of the duration and peak of the QRS complexes from the four areas.

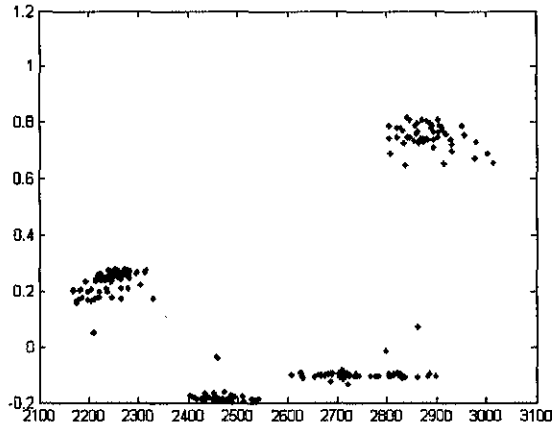

Figure 5.18: Classification of the QRS complexes from the four areas.

The accuracy is found to be 94.5378%. This keeps changing due to the random pick for the testing and training data values during the cross validation. The average accuracy was approximately around 93.5%. A certain set of duration and peak of the QRS complexes were tested again after classification to see if they are correctly classified. As an example, the result is shown below:

e =

1.0e+003 *

2.8550	0.0007
2.9300	0.0007
2.8070	0.0007
2.9770	0.0007
3.0020	0.0007
3.0130	0.0007
2.4550	-0.0002
2.4850	-0.0002
2.4330	-0.0002
2.4590	-0.0002
2.4520	-0.0002

label =

3
3
3
3
3
3
4
4
4
4
4

3 and 4 denotes the pulmonic and tricuspid area respectively. All the signals were correctly classified and hence all the EKG signals can be tracked and it shows the area from which the signal was obtained.

CHAPTER 6

CONCLUSION AND FUTURE WORK

5.1 Conclusions

This research proposed a new method of tracking the heart EKG signal using a virtual pathology stethoscope which will enhance the capabilities of the standardized patients by providing a non-invasive, natural, harmless and realistic appearing tracking method for virtual pathology stethoscope. The EKG signals are recorded and processed to obtain individual QRS complexes, which provides two parameters duration and peak that are then classified to determine the correct position of the stethoscope head on a SP's torso. Cross-validation method and KNN classifier results showed 94.5% accuracy and were able to correctly classify the signals being tested that later determined the correct position of the stethoscope head. It is cost effective and can be used by medical students for much enhanced clinical training.

5.2 Future Work

Future work involves encoding this code into a chip and connecting it to the already built-in chip circuitry so that it can be used in real time by the doctors and medical students for improving their clinical skills.

Multiple subjects' data are to be recorded and the result has to be analyzed. This gives a scope of a much wider analysis of the recorded EKG data.

Also, the variation in the results has to be checked when the orientation of the stethoscope head is changed. This has to be done to check if there is any variation in the EKG signal when the orientation of electrodes is changed.

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APPENDIX A

```
% Appendix A
%The following is the MATLAB code to plot the original signals.
% ***********************************************
% This code was implemented from the paper by Pablo Gomez [8], on "EKG signal processing: An
%Algorithm to detect align QRS complexes".
% Script to load EKG signals from file
% and plot signals (sampling rate = 44100 Hz)
clc;
close all;
clear all;
% plot signal 1:
[y5, Fs, nbits] = wavread('tricuspid2.wav');
    figure;
    plot((1:length(y5))/Fs, y5(:,1));
    xlabel('Time in seconds');ylabel('Amplitude in millivolts');

% process EKG signal 5:
 [qrs,f1]=findqrs(y5);
  %break;
 [QRS,avgbeat,n]=getavgbeat(qrs,f1,1);
 [RRavg1,RRdev1,RRppm1]=beatstat(QRS)
figure;plot(1/44100:1/44100:26460/44100,avgbeat);grid on;
title('Average Beat for EKG Signal at tricuspid area2');
xlabel('Time in seconds');ylabel('Amplitude in millivolts');
printqrs(QRS,'ekg5.txt');
% process EKG signal 5:
[qrs,f1]=findqrs(y5);
[QRS, avgbeat,n]=getavgbeat(qrs,f1,1);
figure;plot(1/44100:1/44100:26460/44100,avgbeat);grid on;
title('Average Beat for EKG Signal at tricuspid area2');
xlabel('Time in seconds');ylabel('Amplitude in millivolts');
[QRS, avgbeat,n]=getavgbeat(qrs,f1,2,avgbeat);
hold on;
figure;
plot(1/44100:1/44100:26460/44100,avgbeat,'r');
[RRavg1,RRdev1,RRppm1]=beatstat(QRS)
printqrs(QRS,'ekg5A.txt');
plot_beats(QRS,f1);

% FINDQRS:
% FUNCTION: findqrs
% this function finds all possible QRS complexes in an EKG signal
% provided as input.
% This code was implemented from the paper by Pablo Gomez [8], on "EKG signal processing: An
%Algorithm to detect align QRS complexes".
%modifications include normalization, 500 point average, finding peak and code for negative peaks.
% INPUTS = ekg (vector containing the EKG signal)
% OUTPUTS = QRS a 32x3 matrix containing the qrs complexes
% column 1 = onset, column 2 = offset, column 3 = duration
% f1, the filtered smoothed EKG signal
function [QRS,f1]=findqrs(ekg)
% Lowpass Filter:
```

```
fs = 44100; % sampling rate = 44100 Hz
fc = 23;    %cutoff frequency = 23 Hz
[B,A]=butter(5,fc/(fs/2), 'low'); % butterworth low-pass filter order 5
t1=filter(B,A,ekg); % filter input signal
figure;
plot((1:length(t1))/fs, t1(:,1));
xlabel('Time in seconds');ylabel('Amplitude in millivolts');
grid on;

% Smooth the filtered signal using a Five Hundred Point Average
f1=zeros(1,length(ekg));
for i=251:length(ekg)-500
   total = 0;
   for j=i:i+500
      total = total + t1(j);
   end
   f1(i-250)=total/500;
 end
 a= max(f1);
b=-(min(f1));

switch max(a,b)
   case a  % positive peak
   k = 1; % number of QRS complexes found (index to QRS)
   N = 882; % number of consecutive monotonically increasing points
   QRS = zeros(32,8); % QRS matrix
   counter = 0; % count number of monotonically increasing points
   find_onset = 1; % Mode = 1 (find onset) Mode = 0 (find offset)
   thr =0.32*max(f1); % threshold (32% of maximum amplitude)    //max
    thcnt=0; % counter of points found above threshold
  [z, RR_v] = find_peak(f1',N); % finding the peak of the QRS complexes.
    for i=3:length(f1)
    % find onset mode
      if find_onset == 1
        if (f1(i) > f1(i-1)) % monotonically increasing point?  //>
        counter=counter+1;
          if counter == N % prospect QRS onset found
          onset = i-N; % the onset is located N points before
          find_onset = 0; % switch mode to find the offset
          thcnt = 0;
          counter = 0;
          val = f1(i-N); % amplitude at onset point
          QRS(k,4)=val;
          QRS(k,1) = onset; % store onset in QRS matrix
          end
        else
        % the amplitude went down, start all over again:
        counter=0;
        end
        %searching for offset mode:
      else
         if f1(i) > thr % count number of points reaching    //>
         thcnt=thcnt+1; % the threshold, after a QRS onset
         end % has been found
         counter=counter+1;
           if counter >= 1838 & thcnt == 0 % 15 points = 41.7ms (15/360)
```

```
          % false onset (after 15 points the threshold was not reached)
          find_onset=1; % switch to find onset mode
          counter=0;
         else
          % this is a QRS complex; look for the offset:
           if f1(i) <= val % if amplitude falls below the  //<=
             if thcnt >= 2 % the onset amplitude, we found the offset
             offset = i;
             QRS(k,5)=f1(i);
             QRS(k,2) = offset; % store offset in QRS matrix
             duration = (offset-onset);
             QRS(k,3) = duration; % store duration in QRS matrix
             QRS(k,6) = (QRS(k,4)+QRS(k,5))/2;
             QRS(k,7)=z(k,1);
             QRS(k,8)=(QRS(k,7)-QRS(k,6)); % normalization
             k = k+1; % next QRS complex
             end
             find_onset=1; % switch back to find onset mode
             counter=0;
           end
          end
      end
    end

   case b % negative peak
k = 1; % number of QRS complexes found (index to QRS)
N = 882; % number of consecutive monotonically decreasing points
QRS = zeros(32,8); % QRS matrix
counter = 0; % count number of monotonically decreasing points
find_onset = 1; % Mode = 1 (find onset) Mode = 0 (find offset)
thr =0.32*min(f1); % threshold (32% of maximum amplitude)    //min
thcnt=0; % counter of points found above threshold
[z, RR_v] = find_peak(f1',N);
 for i=3:length(f1)
  % find onset mode
      if find_onset == 1
          if (f1(i) < f1(i-1)) % monotonically decreasing point?      //<
          counter=counter+1;
            if counter == N % prospect QRS onset found
              onset = i-N; % the onset is located N points before
              find_onset = 0; % switch mode to find the offset
              thcnt = 0;
              counter = 0;
              val = f1(i-N); % amplitude at onset point
              QRS(k,4)=val;
              QRS(k,1) = onset; % store onset in QRS matrix
            end
          else
          % the amplitude went down, start all over again:
          counter=0;
     end
      %searching for offset mode:
     else
        if f1(i) < thr % count number of points reaching          //<
         thcnt=thcnt+1; % the threshold, after a QRS onset
         end % has been found
```

```
        counter=counter+1;
    if counter >= 1838 & thcnt == 0 % 15 points = 41.7ms (15/360)
      % false onset (after 15 points the threshold was not reached)
      find_onset=1; % switch to find onset mode
      counter=0;
    else
      % this is a QRS complex; look for the offset:
      if f1(i) >0 & f1(i) < f1(i-1) % if amplitude falls below the
       if thcnt >= 2 % the onset amplitude, we found the offset
         offset = i;
         QRS(k,5)=f1(i);
         QRS(k,2) = offset; % store offset in QRS matrix
         %printf('***********Negative QRS*************/n');
         duration = (offset-onset);
         QRS(k,3) = duration; % store duration in QRS matrix
         QRS(k,6) = (QRS(k,4)+QRS(k,5))/2;
         QRS(k,7)=z(k,1);
         QRS(k,8)=(QRS(k,7)-QRS(k,6)); % normalization
         k = k+1; % next QRS complex
         end
       find_onset=1; % switch back to find onset mode
       counter=0;
      end
    end
end
end
end
%*********** end of function ***************************************

% GETAVGBEAT:
% FUNCTION: getavgbeat
% this function finds all possible QRS complexes in an EKG signal
% provided as input.
% This code was implemented from the paper by Pablo Gomez [8], on "EKG signal processing: An
%Algorithm to detect align QRS complexes".
% INPUTS = qrs matrix obtained previously by findqrs (prospect QRS)
% f1, the filtered smoothed EKG signal
% templ_type (1=use shortest QRS 2=provided as input parm
% templ, the template QRS when templ_type = 2
% OUTPUTS = QRS a 32x3 matrix containing the aligned qrs complexes
% (column 1 = onset, column 2 = offset,
% column 3 = correlation coefficient,
% column 4 = 1 admitted - 0 rejected)
% avgbeat, the average beat vector
% n, the number of beats aligned and averaged
function [QRS,avgbeat,n]=getavgbeat(qrs,f1,templ_type,templ)
      if templ_type == 1
      % find shortest QRS:
      shortest=999999;
         for k=1:32
           if qrs(k,2) > 0
             if qrs(k,3) < shortest
              shortest = qrs(k,3);
               j=k;
           end
         end
```

```
    end
% Build template (Length=216 points or 600ms;
% Onset at point 76 (35% of 600ms)
     if qrs(j,1)-9260>=0 & qrs(j,1)+17199<=length(f1)
     templ=f1(qrs(j,1)-9260:qrs(j,1)+17199);
     end
end
% Get summation of squares of template points (used later by correlation coeff)
sum_templ=0;
for k=1:26460
     sum_templ=sum_templ+templ(k)^2;
end
% Correlate the template with all QRS complexes found:
QRS=zeros(32,5);
for k=1:32
        % The criteria to admit a QRS complex is as follows:
        % duration >= 36ms (13/360) and <= 94ms (34/360)
        if qrs(k,3) >= 1587 & qrs(k,3) <= 4145
        x=qrs(k,1); % onset of current QRS
        max_corr=0; % Max correlation value
        h=x; % alignment point starts at x
          for m=x-10:x+10
          corrv=0; % correlation value
            for n=1:26460
                if (m+n-9261) > 0 & (m+n-9261) <= length(f1)
                corrv = corrv + templ(n)*f1(m+n-9261);
                end
            end
              if corrv > max_corr
              max_corr = corrv; % Max correlation value
              h=m; % position of max correlation
              end
          end
       % Summation of squares of ekg points in the template window:
          sum_x=0;
            for p=(h-9260):h+17199
             if  p<=length(f1) & p>0
               sum_x=sum_x+f1(p)^2;
            end
     end
     corr_factor = max_corr/sqrt(sum_x*sum_templ);
      % store the alignment and coefficient factor in QRS:
     QRS(k,1)=h;
     QRS(k,2)=h+qrs(k,3);
     QRS(k,3)=max_corr/sqrt(sum_x*sum_templ);
     QRS(k,5)=qrs(k,8);
      % criteria to admit the QRS is correlation factor >= 50%
    if corr_factor >= 0.5
      QRS(k,4) = 1; % admitted
      else
      QRS(k,4) = 0; % rejected
      end
    end
end
% Compute Average Beat:
avgbeat=zeros(1,26460); % 216 == 600ms (216/360)
```

```
n=0;
for k=1:32
if QRS(k,4) == 1
 if  QRS(k,1)-9260>=0 & QRS(k,1)+17199<=length(f1)
   beat = f1(QRS(k,1)-9260:QRS(k,1)+17199);
avgbeat = avgbeat + beat;

 end
           n=n+1;
          end
       end
           if n > 0
           avgbeat=avgbeat/n;
end
%****** END OF FUNCTION ****************************

% FIND PEAK:
% FUNCTION: find_peak
% this function finds all possible peaks of QRS complexes in an EKG %signal
% This code was implemented for finding the peak.
function [z, RR_v] = find_peak(f1,N)
% m is size of neighborhood
m=5000;
SIZE = size(f1);
% y is the output vector -  peak_amplitude where there is a peak
%                    0 o/w
y=zeros(SIZE);
SIZE = SIZE(1);
MAX = max(f1);
MIN = min(f1);
%init RR_counter
RR_c = 1;
%start at 1+m finish at size-m
first = 1;
z = zeros(32,1);
k=1;
a= max(f1);
b=-(min(f1));
switch max(a,b)
  case a
for i = (m+1):(SIZE-m)
good = 1;
  if f1(i) >0.5*MAX
    for j = 1:m
      if (f1(i) <= f1( i -j)) | (f1(i) < f1(i+j))
      good = 0;
      break;
      end;
    end;
    if good
      y(i) = f1(i);
      z(k,1)=y(i);
      k=k+1;
      if (first == 1)
        first = 0;
        RR_v(RR_c) = i;
```

```
        else
          RR_v(RR_c) = i - sum(RR_v);
        end;
      RR_c = RR_c + 1;
      else
        y(i) = 0;
      end;
    else
      y(i) = 0;
    end;
end;

    case b
      for i = (m+1):(SIZE-m)
good = 1;
    if f1(i) <0.5*MIN
      for j = 1:m
        if (f1(i) >= f1( i -j)) | (f1(i) > f1(i+j))
        good = 0;
        break;
        end;
      end;
      if good
        y(i) = f1(i);
        z(k,1)=y(i);
        k=k+1;
         if (first == 1)
           first = 0;
           RR_v(RR_c) = i;
        else
           RR_v(RR_c) = i - sum(RR_v);
        end;
      RR_c = RR_c + 1;
      else
        y(i) = 0;
      end;
    else
      y(i) = 0;
    end;
end;
end;
x = 1:SIZE;
plot(x,y,'x',x,f1);
xlabel('Time in seconds');ylabel('Amplitude in millivolts');
%****** END OF FUNCTION ****************************

% BEATSTAT
% ------------------------------------------------------------------
% FUNCTION: beatstat
% this function calculates the statistics of the EKG signal whose
% QRS matrix is passed as input parameter
% This code was implemented from the paper by Pablo Gomez [8], on "EKG signal processing: An
%Algorithm to detect align QRS complexes".
% INPUTS = qrs (matrix obtained with getavgbeat)
% OUTPUTS = RRavg (average R-R in seconds)
% RRdev (standard deviation of R-R in seconds)
```

```
% RRppm (cardiac rhythm in pulses per minute)
function [RRavg,RRdev,RRppm]=beatstat(qrs)
RR=zeros(1,length(qrs));
m=0;
for k=2:length(qrs)
   if qrs(k,4) == 1
      m=m+1;
if qrs(k,1) > 0 & qrs(k-1,1) > 0
RR(m)=qrs(k,1) - qrs(k-1,1); % RR interval
end
    end
   end
RRavg=mean(RR(1:m))/44100; % sampling frequency = 360 Hz
RRdev=std(RR(1:m))/44100;
RRppm=60/RRavg;
%**** end of function ********

% PLOTBEATS:
% This function plots each QRS complex found on an EKG signal
% This code was implemented from the paper by Pablo Gomez [8], on "EKG signal processing: An
%Algorithm to detect align QRS complexes".
function plot_beats(qrs, f1)
Y1=min(f1)-0.0005;
Y2=max(f1)+0.0005;
figure;
for k=1:12
   if qrs(k,2) > 0 & qrs(k,1)-9260>=0 & qrs(k,1)+17199<=length(f1)
   t=qrs(k,1)-9260:qrs(k,1)+17199;
   subplot(4,3,k);plot(t,f1(t));grid on;
   X1=(qrs(k,1)-9260);
   X2=qrs(k,1)+17199;
   axis([X1 X2 Y1 Y2]);
   end
end
figure;
for k=13:24
    if qrs(k,2) > 0 & qrs(k,1)-9260>=0 & qrs(k,1)+17199<=length(f1)
    t=qrs(k,1)-9260:qrs(k,1)+17199;
    subplot(4,3,k-12);plot(t,f1(t));grid on;
    X1=(qrs(k,1)-9260);
    X2=qrs(k,1)+17199;
    axis([X1 X2 Y1 Y2]);
    end
end
figure;
for k=25:32
     if qrs(k,2) > 0 & qrs(k,1)-9260>=0 & qrs(k,1)+17199<=length(f1)
     t=qrs(k,1)-9260:qrs(k,1)+17199;
     subplot(4,2,k-24);plot(t,f1(t));grid on;
     X1=(qrs(k,1)-9260);
     X2=qrs(k,1)+17199;
     axis([X1 X2 Y1 Y2]);
     end
end
%**** end of function ********
```

```
%PRINTQRS:
% This code was implemented from the paper by Pablo Gomez [8], on "EKG signal processing: An
%Algorithm to detect align QRS complexes".

function printqrs(qrs,filename)
fid=fopen(filename,'w');
for k=1:length(qrs)
    if qrs(k,1) > 0
    fprintf(fid,'%d, %d, %d, %d\r\n',qrs(k,1),qrs(k,2),qrs(k,5),qrs(k,4));
    end
end
fclose(fid);
% *** end of function *****

% CLASSIFICATION
% ----------------------------------------------------------------
% this code is implemented to classify the signals.
close all;
clear all;
clc;
tes=[];
 s=load('EKG2lead.txt'); % loading the values of onset, offset, peak and class  id of the QRS complexes.
 q(:,1)=s(:,2)-s(:,1);
 r=s(:,4);
% classifying the data into four classes corresponding to four areas of the heart.
   for i=1:238
          if r(i)>=1&r(i)<=6
           r(i)=1;
          end
          if r(i)>=7&r(i)<=12
          r(i)=2;
          end
          if r(i)>=13&r(i)<=17
          r(i)=3;
          end
          if r(i)>=18&r(i)<=20
          r(i)=4;
         end
    end
q(:,3)=r;
q(:,2)=s(:,3);
% Plotting the detected QRS complex data.
 x1=find(q(:,3)==1);
x2=find(q(:,3)==2);
x3=find(q(:,3)==3);
x4=find(q(:,3)==4);
plot(q(x1,1),q(x1,2),'r.')
hold on;
plot(q(x2,1),q(x2,2),'g.')
plot(q(x3,1),q(x3,2),'b.')
plot(q(x4,1),q(x4,2),'k.')
hold off;
% 5-fold crossvalidation.
fold = 5;
numData = size(q,1);
rand('state',sum(100*clock))
```

```
partition = ceil(rand(numData,1)*fold);
 fid=fopen('suj.txt','w'); %
 for i=1:238
    fprintf(fid,'%f %f %f',q(i,1:3));
    fprintf(fid,'\n');
 end
 fid = fopen('suj.txt','r');
%saving the training and testing data set in separate file.
for i = 1:5
   fidtrain = fopen('Train.csv','w');
   fidtest = fopen('Test.csv','w');
   fseek(fid,0,-1); %rewinds the file
   for j = 1:numData
      Tline = fgets(fid);
      if partition(j) == i
         fprintf(fidtest,'%s',Tline);
      else
         fprintf(fidtrain,'%s',Tline);
      end
   end
    fclose(fidtrain); fclose(fidtest);
   train_knn=load('Train.csv');
   train_knn = double(train_knn);
   labels = train_knn(:,3);
    test_knn=load('Test.csv');
  testlabel{i}=knnclassify(test_knn(:,1:2),train_knn(:,1:2),labels,3); %knn classification
   Orig=load('Test.csv');
   tes=[tes;Orig(:,1:3)];
   Orig_label{i}=Orig(:,3);
   delete('Train.csv');
   delete('Test.csv');
end
fclose(fid);
lab=[];
test=[];
test=tes(:,1:2);
test(:,3)=cell2mat(testlabel');
% Plotting the classified data.
s1=find(test(:,3)==1);
s2=find(test(:,3)==2);
s3=find(test(:,3)==3);
s4=find(test(:,3)==4);
figure,plot(test(s1,1),test(s1,2),'r.')
hold on;
plot(test(s2,1),test(s2,2),'g.')
plot(test(s3,1),test(s3,2),'b.')
plot(test(s4,1),test(s4,2),'k.')
hold off;
c=0;lab=cell2mat(testlabel');
for i=1:238
     if tes(i,3)==lab(i)
       c=c+1;
     end
end
acc=c/238*100
 % testing the classification
```

```
e=[2855,0.734249600000000;2930,0.700326700000000;2807,0.691597700000000;2977,0.672365800000000;3002,0.689226200000000;3013,0.658204600000000;2455,-0.183463000000000;2485,-0.172989600000000;2433,-0.164915100000000;2459,-0.180579300000000;2452,-0.165454200000000;]
label=knnclassify(e,train_knn(:,1:2),labels,3);
label
% *** end of function *****
```

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EDUCATION

- **Master of Science** December 2009
  Old Dominion University, Norfolk, VA
  Major: **Electrical and Computer Engineering,** GPA: **3.56/4.0**

  Related Courses: Wireless Communications, Embedded Systems, Engineering Systems Modeling, Discrete Event Simulation, Machine Learning, Linear systems, Statistical analysis and simulation.

- **Bachelor of Technology** May 2006
  Jawaharlal Nehru Technological University, India
  Major: **Electronics and communication Engineering**, GPA: **3.6/4.0**

EXPERIENCE

- Old Dominion University, Norfolk, VA
  Research Assistant (August 2007- present)
  - Thesis on "EKG tracking for augmented standardized patient virtual pathology stethoscope heart auscultations".
  - A study of "Analytical models for heart EKG electrical signals".
  - Implemented the Circuit for "acquiring electrical signals from the heart".
  - Interacting with doctors and giving presentations.

- Old Dominion University, Norfolk, VA
  Teaching Assistant (August 2008- December 2008)
  - Assist students with the embedded systems course.
  - Assist the professor in grading, project proposals and set up for an embedded systems lab.

PROJECTS

- EKG tracking for augmented standardized patient virtual pathology stethoscope heart auscultations.
- Simulation and analysis of hospital operations using Arena.
- Resource management using Petri nets for a simple project.
- Modeling and analysis of embedded real time systems based on timed Petri nets.
- Wireless communications in medical applications.
- PC based wireless cardiograph.
- Data acquisition system.