A Framework for Remote Patient Monitoring to Diagnose the Cardiac Disorders

Thesis submitted to the

National Institute of Technology Rourkela

in partial fulfillment of the requirements for the degree

of

Master of Technology (Research)

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2015

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&

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Dedicated to my Parents

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30 July 2015

Certificate

This is to certify that the work in the thesis entitled ***"A Framework for Remote Patient Monitoring to Diagnose the Cardiac Disorders"*** by ***Goutam Kumar Sahoo*** is a record of his original research work carried out under our supervision and guidance. He has fulfilled all prescribed requirements for the award of the degree of Master of Technology (R) in Electronics and Communication Engineering. Neither this thesis nor any part of this has been submitted for any degree or academic award elsewhere.

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ACKNOWLEDGEMENTS

It has been a great experience to work under esteemed supervision of Dr. Samit Ari and Dr. Sarat Kumar Patra. I am very much privileged to have them as my research guides. I would like to thank them from the bottom of my heart for their involvement, guidance, most importantly their support and encouragement throughout the project work. I would also like to thank for their suggestions and comments.

I would like to thank my MSC members Prof. K. K. Mahapatra, Prof. P. K. Sahu and Prof. D. Patra for their suggestions and help in due course of project work. I would like to thank Prof. S. Meher, Prof. S. K. Behera, Prof. S. K. Das, Prof. A. K. Swain, Prof. L. P. Roy, and Prof. S. M. Hiremath for inspiring me in many ways. I am also thankful to other faculties and staffs of Electronics and Communication Engineering department for their support.

I would like to mention the names of Prasanta Pradhan, Manab Das, Dipak Ghosh, Pallab Maji, Manas Biswal and all other members of Pattern recognition Lab, and advance communication Lab, for their constant support and co-operation throughout the course of the project. I would also like to thank all my friends within and outside the department for all their encouragement, motivation and the experiences that they shared with me.

Finally, I would like to thank my parents and my elder brother who have given me good moral support and encouragement throughout my study at NIT Rourkela.

Date: *Goutam Kumar Sahoo*

ABBREVIATIONS

AF	Atrial Fibrillation
ANN	Artificial Neural Network
AT	ATtention
AV	Atrioventricular
aVF	Augmented Vector Foot
aVL	Augmented Vector Left
aVR	Augmented Vector Right
AWES	Ambulatory Wireless ECG Sensor
AZTEC	Amplitude Zone Time Epoch Coding
BIH	Beth Israel Hospital (now Beth Israel Deaconess Medical Center)
BPM	Bits Per Minute
CHD	Coronary Heart Disease
CVD	Cardio Vascular Disease
CORTES	Coordinate Reduction Time Encoding System
CR	Compression Ratio
DCT	Discrete Cosine Transform
DPCM	Differential Pulse Code Modulation
DVD-ROMs	Digital Versatile Disc-Read Only Memories
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
EMD	Empirical Mode Decomposition

ESC	European Society of Cardiology
FN	False Negative
FOI-2DF	First-Order Interpolation with two Degrees of Freedom
FP	False Positive
FWT	Fast Wavelet Transform
GB	Gigabyte
GPRS	General Packet Radio Service
GSM	Global System for Mobile communications
HR	Heart Rate
HT	Hilbert Transform
HTT	Hilbert Huang Transform
IDCT	Inverse Discrete Cosine Transform
IF	Instantaneous Frequency
IHD	Ischemic Heart Disease
IMF	Intrinsic Mode Function
JPEG	Joint Photographic Expert Group
KLT	Karhunen-Loeve Transform
LA	Left Arm
LADT	Linear Approximation Distance Thresholding
LL	Left Leg
MATLAB	Matrix Laboratory
MB	Megabyte
MI	Myocardial Infarction
MIT	Massachusetts Institute of Technology
MMS	Multimedia Messaging Service
NN	Neural Network
PC	Personal Computer
PCA	Principal Component Analysis

PDA	Personal Digital Assistant
PDU	Protocol Data Unit
PPA	Positive Predictive Accuracy
PRD	Percent Root Mean Square Difference
PSVT	Paroxysmal Supraventricular Tachycardia
RA	Right Arm
RAM	Random-Access Memory
RECAD	Real-time Continuous Arrhythmias Detection
SA	Sinoatrial
SAPA	Scan-Along Polygonal Approximation
SD	Standard Deviation
Se	Sensitivity
SIM	Subscriber Identity Module
SMS	Short Message Service
SMSC	SMS Center
SNR	Signal-to-Noise Ratio
Sp	Specificity
SPIHT	Set Partitioning In Hierarchical Trees
TDM	Time Division Multiplexing
TIA	Transient Ischemic Attack
TP	True Positive
TP	Turning Point
USB	Universal Serial Bus
WHO	World Health Organization
WPW	Wolff-Parkinson- White

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ABSTRACT

Electrocardiogram (ECG) is an efficient diagnostic tool to monitor the electrical activity of heart. One of the most vital benefit of using telecommunication technologies in medical field is to provide cardiac health care at a distance. Telecardiology is the most efficient way to provide faster and affordable health care for the cardiac patients located at rural areas. Early detection of cardiac disorders can minimize cardiac death rates. In real time monitoring process, ECG data from a patient usually takes large storage space in the order of gigabytes (GB). Hence, compression of bulky ECG signal is a common requirement for faster transmission of cardiac signals using wireless technologies. Several techniques such as the Fourier transform based methods, wavelet transform based methods, etc., have been reported for compression of ECG data. Though Fourier transform is suitable for analyzing the stationary signals. An improved version, the wavelet transform allows the analysis of non-stationary signal. It provides a uniform resolution for all the scales, however, wavelet transform faces difficulties like uniformly poor resolution due to limited size of the basic wavelet function and it is nonadaptive in nature. A data adaptive method to analyse non-stationary signal is based on empirical mode decomposition (EMD), where the bases are derived from the multivariate data which are nonlinear and non-stationary. A new ECG signal compression technique based on EMD is proposed, in which first EMD technique is applied to decompose the ECG signal into several intrinsic mode functions (IMFs). Next, downsampling, discrete cosine transform (DCT), window filtering and Huffman encoding processes are used sequentially to compress the ECG signal. The compressed ECG is then transmitted as short message

service (SMS) message using a global system for mobile communications (GSM) modem. First the AT-command '+CMGF' is used to set the SMS to text mode. Next, the GSM modem uses the AT-command '+CMGS' to send a SMS message. The received text SMS messages are transferred to a personal computer (PC) using blue-tooth. All text SMS messages are combined in PC as per the received sequence and fed as data input to decompress the compressed ECG data. The decompression method which is used to reconstruct the original ECG signal consists of Huffman decoding, inverse discrete cosine transform (IDCT) and spline interpolation. The performance of the compression and decompression techniques are evaluated in terms of compression ratio (CR) and percent root mean square difference (PRD) respectively by using both European ST-T database and Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) arrhythmia database. The average values of CR and PRD for selected ECG records of European ST-T database are found to be 23.5:1 and 1.38 respectively. All 48 ECG records of MIT-BIH arrhythmia database are used for comparison purpose and the average values of CR and PRD are found to be 23.74:1 and 1.49 respectively. The reconstructed ECG signal is then used for detection of cardiac disorders like bradycardia, tachycardia and ischemia. The preprocessing stage of the detection technique filters the normalized signal to reduce noise components and detects the QRS-complexes. Next, ECG feature extraction, ischemic beat classification and ischemic episode detection processes are applied sequentially to the filtered ECG by using rule based medical knowledge. The ST-segment and T-wave are the two features generally used for ischemic beat classification. As per the recommendation of ESC (European Society of cardiology) the ischemic episode detection procedure considers minimum 30s duration of signal. The performance of the ischemic episode detection technique is evaluated in terms of sensitivity (Se) and positive predictive accuracy (PPA) by using European ST-T database. This technique achieves an average Se and PPA of 83.08% and 92.42% respectively.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Current technological advance in medical science has made life better for everyone. Use of wireless technology in medical science provides faster and essential health care. Presently, heart diseases are the most common cause of human death. Abnormality in functioning of heart produces heart diseases. Early detection of heart disorders can offer long life to the heart patients. Electrocardiogram (ECG) is an efficient diagnostic tool to monitor the electrical activity of heart [1]. ECG provides valuable diagnostic information about functioning of heart and cardiovascular system. A patient located at a rural area faces lots of difficulties in getting appropriate treatment due to unavailability of advance equipments and specialist doctors. In this scenario mobile health care and remote health care system is helpful.

Remote health monitoring is a new model of health care service to monitor a patient at home using wireless communication network [2]. In this type of health care, a patient or physician located in a remote location can communicate and discuss with doctors located at a distance [3]. If necessary patient can send the required data immediately to the expert doctors. The purpose of remote health care system is to provide faster and valuable diagnosis to a remote patient. In remote patient monitoring, unnecessary travelling cost and time delay to get proper health care is minimized [4]. Here patient gets proper health care at home from expert doctors without moving from one hospital to another. Hence, remote monitoring offers improved patient safety and quality of health care. In real time cardiac patient monitoring, ECG data from a patient usually takes large storage space in the order of gigabytes (GB) [5]. It is very difficult to store and transfer this bulky ECG signal. Hence, this large amount of ECG data need to be compressed for establishing faster diagnosis through wireless medium. Compression of bulky ECG signal for minimal memory usage and better storage efficiency is an important aspect of signal processing. Moreover, for remote health care systems, the ECG signal is to be compressed sufficient enough so that, it can be transmitted over wireless medium.

Faster data transmission from a patient to a physician or doctor can be possible using wireless technology. In this thesis, a low cost and efficient method based on short message service (SMS) is used to transmit the compressed ECG. The received compressed ECG data are decompressed to reconstruct the ECG signal for immediate diagnosis by experienced physicians or expert doctors. An efficient and faster detection of cardiac disorders are necessary to take preliminary action towards the treatment. One of the important parameter to evaluate a person's health is the heart rate (HR). A healthy person's HR depends on normal rhythm of heart. The heart rhythm defines the speed of the heartbeat. The heart rate is the number of heartbeats per unit of time. Generally HR is measured in beats per minute (bpm). The abnormal heart rhythm causes slow or fast heartbeat. The cardiac disorder, ischemia or heart stroke, affects the heart and the blood vessels. Ischemia occurs due to inadequate blood flow and oxygen to a particular part of the body. It can occur in the limbs, heart, brain, or intestines. The ECG beat classification is essential for automatic detection and diagnosis of heart stroke. ECG Consist of PQRST waveform. The key to detect ischemia is the measurement of ST-segment deviation and change in T-wave amplitude. The abnormal heart rhythms are identified by calculating HR and the performance of the ischemia detection technique is evaluated in terms of sensitivity (Se) and positive predictive accuracy (PPA). The standard ECG data from European ST-T database [6] is used for experimental testing purpose and Massachusetts Institute of Technology-Berth Israel Hospital (MIT-BIH) arrhythmia database [7] is used for comparison purpose.

A wireless tele-cardiology system for transmission of compressed ECG and detection of the cardiac disorders is shown in Figure 1.1. First, ECG signal is compressed using EMD based technique. Next, a GSM modem is used to transmit the compressed ECG as SMS. The received SMS messages are decompressed to reconstruct the original signal. The reconstructed ECG is then analysed to detect the cardiac disorders. Most of the cardiac or heart disorders occurs due to the restriction of blood flow and oxygen to the heart. Detail functioning of heart, electrical conduction of the heart and the cardiac cycle are described in following sections.

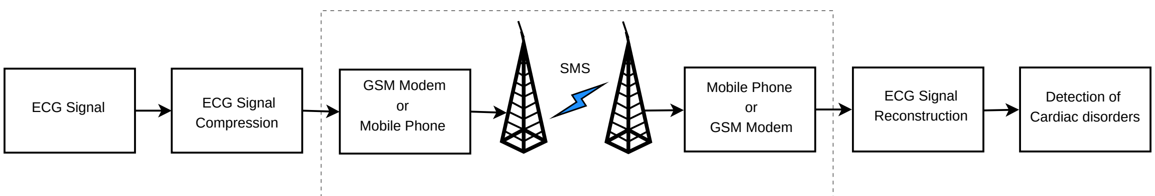

Figure 1.1: Block diagram of wireless tele-cardiology system

1.2 Human heart anatomy

Heart supplies blood throughout the body. It is located between the lungs in the left side of the sternum. A cross sectional view of human heart is shown in Figure 1.2. The heart is made up of four chambers. The upper two chambers are called the left and right atria, while the lower two chambers are called the left and right ventricles [1].

- **Right atrium:** This chamber consists of de-oxygenated blood, that returns from the body, this de-oxygenated blood is then passed on to the right ventricle.

- **Right ventricle:** It is a chamber, that consists of de-oxygenated blood which is passed into the lungs for oxygenation.

- **Left atrium:** This is the chamber, where the oxygenated blood enters from the pulmonary vein. The blood from the left atrium is then forced into the left ventricle.

- **Left ventricle:** The oxygenated blood enters the left ventricle and is then forced from the left ventricle into the aorta. The aorta carries the oxygenated blood from the heart to the other parts of the body.

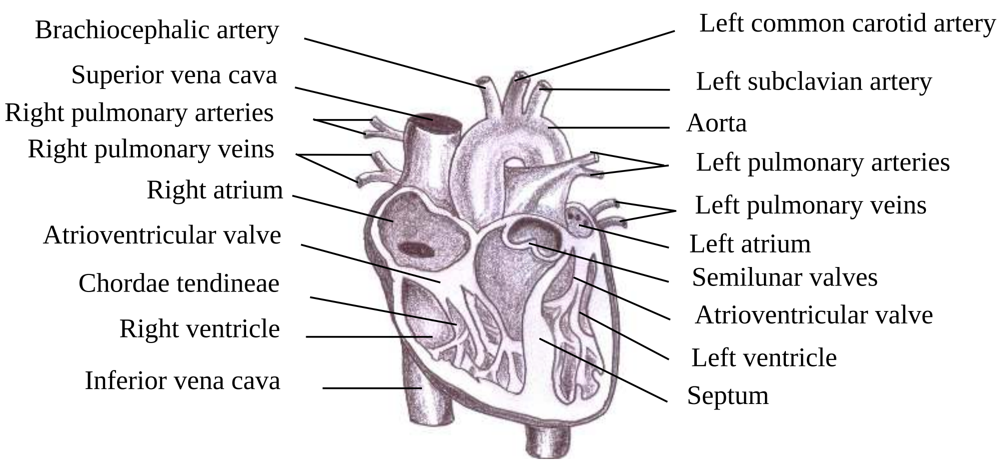

Figure 1.2: Cross section of a human heart

The heart is made of cardiac muscle tissue, that contracts and relaxes throughout the lifetime of a person and this contraction and relaxation of the muscle drives the blood from the heart. The contraction and relaxation of the cardiac muscle is in a rhythm, when the cardiac muscle of the heart's ventricles contract, it is called as systole and when the cardiac muscle of heart's ventricles relax, it is called as diastole [1].

1.3 Electrocardiogram

The electrocardiogram (ECG) has become an essential part for complete medical evaluation on any type of cardiac disease diagnostic test. The ECG waveform allows information about electrical activity associated with different aspects of the heartbeat. The manner in which the heart contracts over time determines the rhythm of the heart.

A normal cardiac rhythm is referred to as a 'sinus' rhythm. Normal sinus rhythm is characterized, that there is no disease or disorder affecting heart. Deviation from this normal sinus rhythm is known as cardiac arrhythmias. The abnormal rhythm can be life threatening. If the heart rate is too slow then pumping of blood to the blood vessels may be insufficient, which affects vital organs else for fast rate, the ventricles are not completely filled before contraction and pumping efficiency drops. Therefore any change in heart rhythm caused by cardiac arrhythmias will reflect in the person's ECG [1]. In General, ECG provides following information [8].

- Position of the heart and the size of the chambers.
- Origin of impulse and its propagation.
- Heart rate and disturbances in conduction.
- Variations in electrolyte concentrations.
- Position of myocardial ischemia.

1.3.1 Basic ECG patterns

ECG shows the electrical activity of the heart. The electrical activity of heart is measured by placing electrodes on the skin of a patient. The wave of electrical activity spreads from the atria to the ventricles. Generation of ECG wave corresponds to a specific part of the heart is shown in the Figure 1.3. The paths of electrical activities are recorded for determination of heart rhythm abnormalities. The waves and segments of the ECG are described as follows.

- **P-wave:** It comes first and represents the depolarization of atria. During this time the electrical impulse starts from SA (sinoatrial) node to AV (atrioventricular) node spreading through both the atria [1].
- **QRS-complex:** This represents the depolarization of ventricles and is the strongest wave in ECG. QRS-complex consists of three peaks: 'Q' and 'S' are negative peaks and 'R' is the positive peak [9].

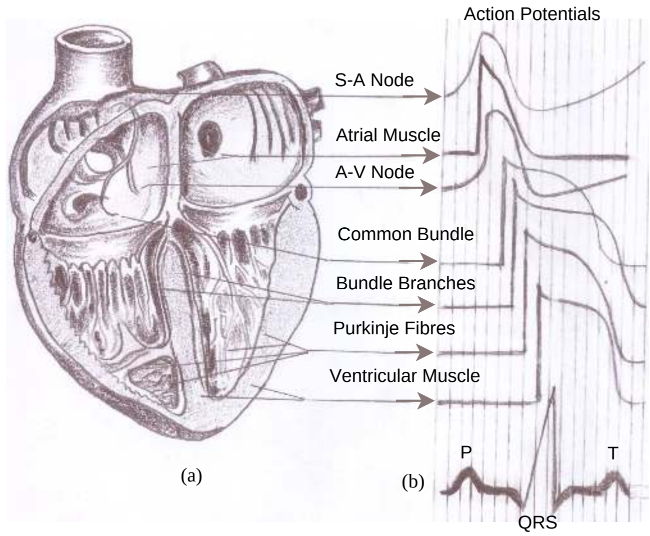

Figure 1.3: (a) Human heart cross sectional view (b) Generation of ECG wave

- **PR-interval:** The delay between P-wave and QRS-complex. During this time, the electrical impulse travels from the atria to the ventricles through the AV node [10].
- **T-wave:** This is a positive defection soon after the QRS-complex and represents repolarization of the ventricles [8].
- **ST-segment:** This is the time duration between S-wave and the outset of T-wave and occurs between the depolarization and repolarization of ventricles. ST-segment always align with the isoelectric line [10].
- **U-wave:** It is a small deflection following T-wave and represents the repolarization of purkinje fibres [10].

A typical ECG wave for one cardiac cycle is shown in the Figure 1.4. Generally, one cycle ECG signal consists of mainly three features i.e. P-wave, QRS-complex, T-wave and U-wave, which is visible sometimes. The baseline (isoelectric line) is the flat horizontal segments of ECG. The baseline is measured as a portion of the tracing following the T-wave to the next P-wave and the PR-segment.

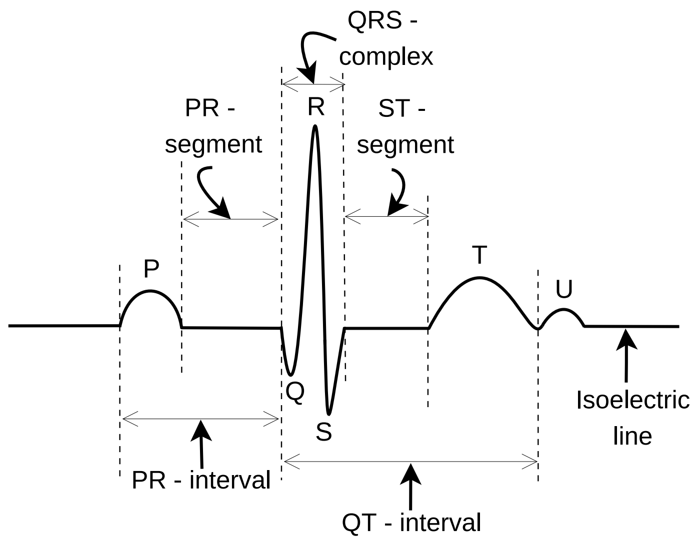

Figure 1.4: One complete ECG cycle

1.3.2 ECG lead placement

A standard clinical ECG consists of 12 different vectors known as “leads". A lead is a particular view of the electrical activity of the heart. The electrical potential are obtained by a pair of electrodes placed at different locations on the body surface and generates different ECG vectors. Figure 1.5 represents the positions of 12 ECG leads. Six leads out of these 12 leads are in the plane parallel to the body and other six ECG leads are views of the heart in the plane perpendicular to the body. A standard 12-lead ECG consist of three bipolar limb leads, three unipolar limb leads and six chest leads.

1.3.2.1 Bipolar Limb Leads

Leads I, II and III belongs to this category. These leads are obtained with electrodes of opposite polarity (+ve and -ve) [10].

- **Lead I:** Difference between left arm (LA) electrode potential and right arm (RA) electrode potential (LA-RA).
- **Lead II:** Difference between left leg (LL) electrode potential and right arm (RA) electrode potential (LL-RA).

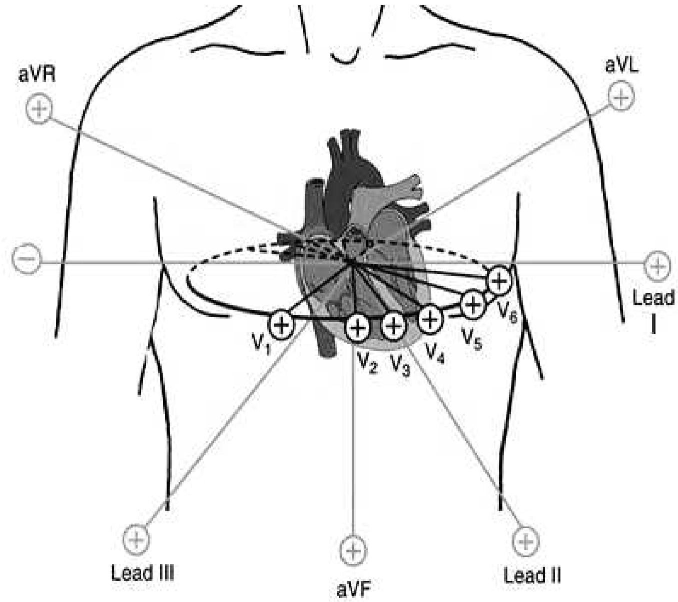

Figure 1.5: Positions of 12 ECG leads

- **Lead III:** Difference between left leg (LL) electrode potential and left arm(LA) electrode potential (LL-LA).

1.3.2.2 Unipolar Limb Leads

Augmented vector right (aVR), augmented vector left (aVL) and augmented vector foot (aVF) are the unipolar limb leads. These leads are obtained with a single positive electrode and a reference point which are lies in the center of heart's electric field [10]. These leads are explained as follows.

- **aVR:** The potential difference between right arm electrode and the center of heart's electric field.
- **aVL:** The potential difference between left arm electrode and the center of heart's electric field.
- **aVF:** The potential difference between left leg and the center of the heart's electric field.

1.3.2.3 Unipolar chest Leads

Leads $V_1 - V_6$ are unipolar chest leads. Here, the positive electrodes of leads $V_1 - V_6$ is placed at specific points on the chest as shown in the Figure 1.5. The leads show the potential difference between the positive electrode and the center of the heart's electric field [10]. The locations of the positive electrodes for $V_1 - V_6$ leads are given below.

- V_1**:** Fourth intercostal space in right side of sternum.
- V_2**:** Fourth intercostal space in left side of sternum.
- V_3**:** Directly between V_2 and V_4.
- V_4**:**Fifth Intercostal space on the left mid-clavicular line.
- V_5**:** In the same level of V_4 at anterior axillary line on the left side.
- V_6**:** In the same level of V_5 at mid-axillary line on the left side.

1.4 Cardiovascular disorders

Heart disease is one of the major cause of death in humans. Inadequate supply of blood and oxygen is one of the most common cause of all heart diseases. World health organization (WHO) in 2008 estimated death of 17.3 million people from cardiovascular diseases (CVD) which represent 30% of all global deaths [11]. Out of all CVD deaths ischemic heart disease (IHD) itself reports 7,249,000 deaths which is 12.7% of total global mortality. Of these IHD deaths, an estimated 7.3 million are due to coronary heart disease and 6.2 million are due to stroke [12]. It is anticipated that by the year 2030, 23.6 million people will die from CVDs. Also it is expected that the worst affected region will be south-east Asia. One of the problems is the poor doctor to patient ratio in the underdeveloped and developing nations. The doctor to patient ratio in India is as low as 60 per one lakh population as compared to more than 250 per one lakh in the developed countries [13]. Sometimes the symptoms for heart disease are difficult to detect and it is not detected until a major issue like heart attack occurs. Sometimes, symptoms are noticeable like chest pain (angina), extreme fatigue and shortness of breath. Several categories of heart disease [14] are given as follows.

- **Coronary heart disease:** It is a condition, in which supply of blood and oxygen to the heart reduced due to formation of plaque in the coronary blood vessels. It is also known as coronary artery disease.
- **Angina pectoris:** It is a medical term for chest pain and it occurs due to insufficient supply of blood to the heart.
- **Congenital Heart Disease:** Commonly known as heart failure. It is a condition, where the heart cannot pump enough blood to the rest of the body.
- **Arrhythmias:** It is a disorder in the rhythmic movement of the heartbeat. The heartbeat can be slow, fast, or irregular.
- **Cardiomyopathy:** It is the condition of weakening the heart muscle or a change in the structure of the muscle due to inadequate heart pumping.
- **Ischemic Heart Disease:** It is a type of coronary artery disease and it results due to reduced blood supply to the heart. Main cause of this disease is atherosclerosis.

1.5 Cardiac dysrhythmia or heart rhythm abnormality

Cardiac dysrhythmia or heart rhythm abnormality is the conditions in which the electrical activity of the heart is irregular [15]. One study by Hsia *et al.* analyzed digitized ECG data in a beat-by-beat mode [16]. Each beat is assigned a beat code based on a combination of waveform analysis and RR-interval measurement for abnormal rhythm analysis. The regular or normal heart rhythm is 60 to 100 beats per minute (bpm) [1]. As stated in [15], a heartbeat that is too slow is called bradycardia and a heartbeat that is too fast is called tachycardia. Heart can not pump enough blood to the body if the heart rate is irregular. Lack of blood flow can damage the brain, heart and other vital organs. The heart's electrical system controls the rate and rhythm of the heartbeat.

1.5.1 Causes

An arrhythmia occurs, if the electrical signals that control the heartbeat are delayed or blocked. This happens, when electrical signals do not travel normally through the heart.

There are various causes of arrhythmia, which are mentioned below.

- Smoking.
- Heavy use of alcohol.
- Use of certain drugs (such as cocaine or amphetamines).
- Too much use of caffeine or nicotine.
- Strong emotional stress or anger leading to raised blood pressure.

1.5.2 Major risk factors

Arrhythmias are more common in people having diseases or different conditions, that weaken the heart. Various risk factors of arrhythmia are mentioned below.

- Heart attack.
- Heart failure or cardiomyopathy.
- Too thick or strong heart tissue.
- Narrow heart valves.
- Congenital heart defects.
- High blood pressure.
- Diabetes.

1.5.3 Symptoms of arrhythmias

Many arrhythmias has no signs or symptoms, whereas some typical common symptoms present includes the following.

- Too hard or fast beating of heart.
- Slow heartbeat.
- An irregular heartbeat.
- Feeling pauses between heartbeats.
- Weakness, dizziness and sweating.
- Shortness of breath.
- Chest pain.

1.5.4 Types of arrhythmia

Most arrhythmias are harmless, whereas some arrhythmia depends on its severity. People having arrhythmias can live normal and healthy lives. Four main types of arrhythmia are reported as follows.

1.5.4.1 Premature (extra) beats

These are most common type of arrhythmias and most of the time, these are harmless. A person usually feels like wavering in the chest or a feeling of a skipped beat. Most of the time, premature beats need no treatment, especially in healthy people.

1.5.4.2 Supraventricular arrhythmias

These type of arrhythmias are tachycardias (fast heart rates), that start in the atria or the atrioventricular (AV) node. Types of supraventricular arrhythmias are atrial fibrillation (AF), atrial flutter, paroxysmal supraventricular tachycardia (PSVT) and wolff-parkinson-white (WPW) syndrome, which are explained as follows.

- During AF, atria are not able to pump blood into the ventricles as the walls of the atria vibrates very fast (fibrillate) instead of beating normally. This spreads electrical signals in a fast and irregular rhythm through the atria.
- During atrial flutter, electrical signals travel in a fast and regular rhythm. Atrial flutter causes and symptoms are similar to AF.
- During PSVT, heart rate is a very fast that begins and ends suddenly. It causes extra heartbeats, which happens during vigorous exercise.
- Wolff-parkinson-white syndrome is a type of PSVT, in which the heart's electrical signals travel along an extra pathway from the atria to the ventricles. This extra pathway disrupts the timing of the heart's electrical signals and causes the ventricles to beat very fast. This type of arrhythmia can be life threatening.

1.5.4.3 Ventricular arrhythmias

These arrhythmias start in the ventricles and usually need medical attention. Ventricular arrhythmias include ventricular tachycardia and ventricular fibrillation (v-fib). These are explained below.

- Ventricular tachycardia is a fast, regular beating of the ventricles, that may last for only a few seconds. An episodes, that last for more than a few seconds can be dangerous.
- V-fib occurs, when disorganized electrical signals make the ventricles vibrate instead of pump normally. This is dangerous as ventricles unable to pumping blood out of the body. A person may lose consciousness within seconds and die within minutes if not treated. This happen during or after a heart attack.

1.5.4.4 Bradyarrhythmias

In these arrythmia the heart rate is much slower than normal. This slow heart rate can not supply required amount of blood to brain. This situation leads loss of consciousness. In bradyarrhythmia disease, the heart rate is usually less than 60bpm for adults.

1.6 Cardiac ischemia or Ischemic heart disease

Ischemic heart disease is the most common type of heart disease and a cause of heart attacks [14]. The disease is caused by plaque building up along the inner walls of the arteries of the heart, which narrows the arteries and reduces blood flow to the heart. Ischemia is a condition of relative shortage of oxygen and other nutrients in the supplied blood to any organ, that damages the tissue. Ischemia may occur in body parts including the limbs, heart, brain or intestines.

1.6.1 Cardiac ischemia categories

Cardiac ischemia are broadly categories as angina and myocardial infarction, which are explained as follows.

1.6.1.1 Angina

Angina is a serious chest pain caused by an imbalance between myocardial blood supply and oxygen demand. The main cause of angina is atherosclerosis in the cardiac arteries.

1.6.1.2 Myocardial infarction

Myocardial infarction (MI) is commonly known as a heart attack. It occurs, when the blood flow suddenly stops causing heart cells to die. This is most commonly due to blockage of a coronary artery by plaque build up. The resulting ischemia and oxygen shortage can damage or may lead to death (infarction) of heart muscle tissue.

1.6.2 Causes

Ischemic heart disease is caused by blockage of an artery due to plaque formation, usually called atherosclerosis. Plaque formation narrows the artery, which makes blood to clot easily and completely block the arteries. There are various causes of ischemic heart disease, which are mentioned below.

- Ventricular tachycardia.
- Compression of blood vessels.
- Atherosclerosis.
- Extremely low blood pressure.
- Congenital heart defects.
- Sickle cell anemia.

1.6.3 Major risk factors

There are several major risk factors, which are mentioned below.

- Overweight and obesity.
- Smoking.
- Diabetes.
- Hypertension.

- Stress.
- High blood cholesterol.
- Drug abuse.
- Lack of physical activity.
- Coronary artery disease.

1.6.4 Different types of ischemia

Ischemia is classified into different types depending on the affected areas of the body parts. Some major types are (i) Cardiac ischemia, (ii) Cerebral ischemia, (iii) Intestinal ischemia, (iv) Critical limb ischemia.

1.6.4.1 Cardiac ischemia

In cardiac ischemia or myocardial ischemia flow of blood to the heart muscle is limited by the blockage of a coronary artery. A sudden and severe blockage due to plaque may lead to heart attack. Cardiac ischemia may also cause angina and arrhythmia. Following are the typical symptoms of a myocardial ischemia.

- Difficulty in breathing.
- Pain in arm.
- Pain in chest.
- Pain in neck.
- Pain in jaw.

1.6.4.2 Cerebral ischemia

This type of ischemia takes place in the arteries of the brain due to restriction of blood flow. A plaque is formed by blood clot in cerebral arteries. This plaque narrows down the artery and blocks blood flow to brain. Some of the symptoms involved with cerebral ischemia are mentioned below.

- Weakness.

- Unconsciousness.
- Difficulty speaking.
- Vision disability.
- Blindness.
- Body movement problems.

1.6.4.3 Intestinal or Bowel ischemia

Ischemic bowel disease occurs due to narrowing of the arteries, which leads to low supply of oxygen needed to the intestines. The reduced blood flow may cause pain. This type of ischemia may damage the intestine. Sign and symptoms of bowel ischemia [17] are mentioned below.

- Sudden abdomen pain.
- Blood in stool.
- Black stool.
- Diarrhea.
- Constipation.

1.6.4.4 Critical limb ischemia

Critical limb ischemia occurs due to serious decrease in blood flow to hands, feet and legs. Critical limb ischemia is often involved with severe peripheral arterial disease. Following are the major symptoms of this type of ischemia.

- Severe pain in feet or toes even person is not moving.
- Thickening of the toenails.
- Skin infections or ulcers.
- Dry, black skin of the legs.

1.7 ST-segment analysis of ECG

Cardiac ischemia causes fluctuations in T-wave and ST-level of ECG. The ST-level change episodes are useful for disease detection and diagnosis. Most of the clinically useful information are found in the intervals and amplitudes of ECG waves. The characteristic features of ECG are the peak detection and time durations calculation. An ECG graph with different peaks and intervals is shown in Figure 1.6. In a normal ECG, the S-point is the first inflection point after R-peak. S-point is identified by determining the change in slope. ST-slope is the important characteristic of ECG signal to investigate myocardial ischaemia. Elevation or depression of ST-segment provides important features for detection of myocardial ischemia. Generally, ST-level is used to identify ischaemic episodes. Elevation and depression of ST-segment together with changes in T-wave amplitude can indicate the ischaemic disorder. ST-level deviation is measured from the isoelectric level. The normal range of different waves and segments associated with ECG are described in the Table 1.1.

Table 1.1: Description of different waves and segments in a ECG cycle

ECG Features	Amplitude (mV)	Duration (ms)	Description
P-wave	0.1 - 0.25	60 - 80	The P-wave is the first wave of ECG and represents the sequential activation of the right and left atria.
PR-segment	-	50 - 120	The PR-segment is the flat, usually isoelectric segment between the end of the P-wave and the start of the QRS-complex.
PR-Interval	-	120 - 200	The PR-interval is the time duration from the beginning of P-wave to the beginning of QRS-complex.
QRS-complex	1	80 - 120	The QRS represents the simultaneous activation of the right and left ventricles.
ST-segment	-	80 - 120	The ST-segment follows the QRS-complex. The point at which it begins is called the J-(junction) point.
T-wave	0. 1 - 0.5	120 - 160	The T-wave represents the period of recovery for the ventricles .
ST-Interval	-	320	The ST-interval is measured from the J-point to the end of the T-wave.
QT-interval	-	300 - 430	The QT-interval is measured from the beginning of the QRS-complex to the end of the T-wave.
RR-Interval	-	600 - 1200	The time elapsing between two consecutive R-waves in the electrocardiogram.

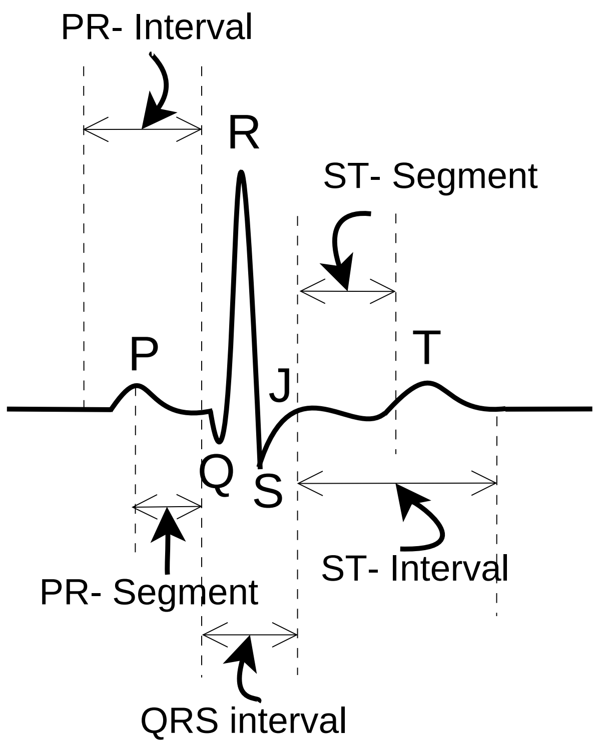

Figure 1.6: ECG graph with different peaks and intervals

1.7.1 ST-segment elevation

ST-elevation is a measurement on an ECG, in which the trace in the ST-segment is very high above the isoelectric line. It identifies silent ischemia known as heart attack. During heart attack, the coronary artery is blocked by the blood clot. This makes the heart muscle to die. The changes in ECG characteristics identifies severe heart attack. ST-segment elevation is one of the changes in ECG, where large amount of heart muscle damage occurs. When ST-deviation is more than 0.08mV above the isoelectric line, it is considered as positive ST-deviation or ST-elevation. The Figure 1.7 shows an elevated ST-segment.

1.7.2 ST-segment depression

ST-segment depression is reciprocal of ST-elevation. The depression of ST-segment is caused by rapid heart rate, electrolyte abnormality and ischemia. Change in the ST-

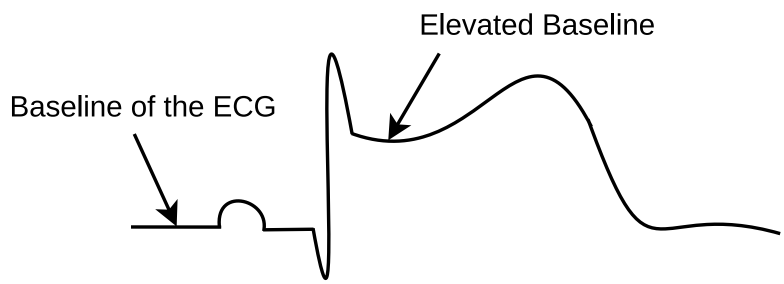

Figure 1.7: ST-segment elevation

segment shape allows diagnosis of ST-depression. ST-deviation of more than 0.08mV below the isoelectric line is considered as negative ST-deviation or ST-depression. ST-segment depression is shown in Figure 1.8.

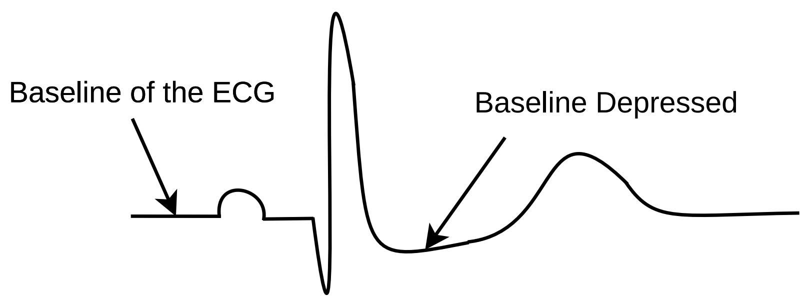

Figure 1.8: ST-segment depression

1.7.3 T-wave

The normal duration of T-wave in ECG is 120-160ms [1]. The amplitude changes in T-wave is also a distinguished factor for ischemic episodes detection. The abnormal T-wave is usually very tall. It also appears as inverted corresponding to the elevation or depression in ST-segment. The T-wave inversion or flattening is generally measured using first 30s of the ECG recording. Different types of T-wave amplitude variations are shown in the Figure 1.9.

1.7.4 Isoelectric line

The flat horizontal segments is the base or isoelectric line in an ECG cycle. It is the portion of ECG between the end of T-wave and start of P-wave or between the end of

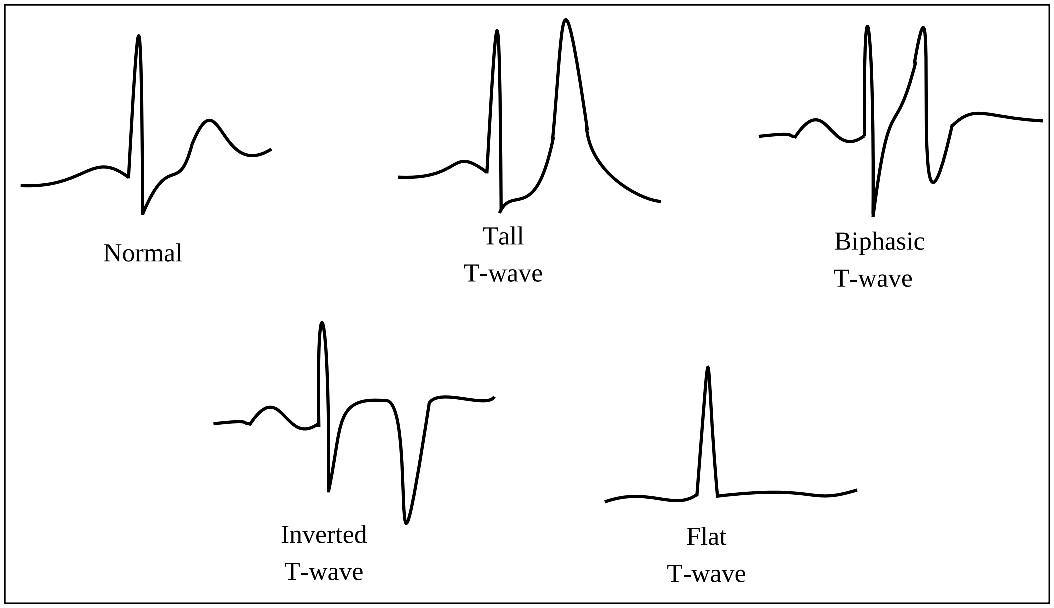

Figure 1.9: T-wave alternation

P-wave and QRS-complex. The baseline is equivalent to 0mV line in a normal healthy heart. The baseline may be depressed or elevated relative to the ST-segment in case of heart disorders. The variation of ST-segment remains close to the isoelectric line. The level of ST-segment is determined with respect to isoelectric level. If ST-segment is below the baseline, then it is called ST-depression. During ST-depression, myocardium is not getting enough oxygen which leads to myocardial ischemia. If the level of ST-segment is above the baseline, then it is known as ST-elevation which leads to myocardial infarction. The Figure 1.10 shows the position of isoelectric line in ECG signal.

1.8 European ST-T ECG database

The European ST-T database is used for evaluation of the proposed techniques. This database consists of 90 annotated selections of ambulatory ECG recordings from 79 subjects. Myocardial ischemia was suspected for each subject and additional selection criteria were established to identify ECG abnormalities in the database. The baseline ST-segment displacement criteria was established from the conditions like hypertension, ventricular dyskinesia and effects of medication. The database includes 367 episodes of ST-segment change and 401 episodes of T-wave change, with durations ranging from 30 seconds to several minutes and peak displacements ranging from 100 microvolts to more than one millivolt. Also this database includes 11 episodes of axis shift which results apparent ST-change and 10 episodes of axis shift which results apparent T-wave change. Each record is of two hours in duration and consists two signals, each sampled at 250 samples per second with 12-bit resolution over a nominal 20 millivolt input range. Two cardiologists worked independently to annotate each record beat-by-beat and for changes in ST-segment and T-wave morphology, rhythm and signal quality. ST-segment and T-wave changes were identified in both leads and their onsets, extrema and ends were annotated [6].

1.9 Mobile health care

A term used for the practice of medicine and public health supported by mobile devices like mobile phones, tablet computers, personal digital assistants (PDAs) etc., is known as mobile health or m-health [18]. The field of m-health broadly encompasses, the use of mobile telecommunication and multimedia technologies in health care delivery [19]. The term m-health was introduced by Robert Istepanian as use of "emerging mobile

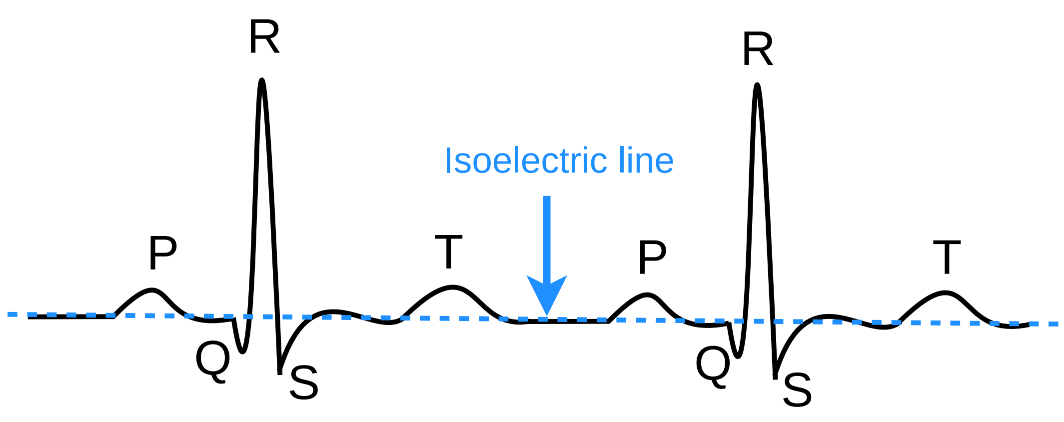

Figure 1.10: ECG graph showing isoelectric line

communications and network technologies for health care" [20]. The development of the m-health arises from the constraints which includes the following.

- high population growth, high burden of diseases, low health care workforce, large numbers of rural patients and limited financial resources to support health information systems [21].
- rapid rise in mobile phone technology and availability of advanced health care infrastructure mobile phone can deliver health care to the rural people at low cost [20].

The objectives of m-health care are as follows.

- Increased access with low cost effective health care.
- Improved ability to diagnose and detect diseases.
- More public health information with for immediate action.
- Expanded access to ongoing medical education and training for health workers.

The short message service (SMS) or multimedia messaging service (MMS) and real-time voice communication technology are the backbone of mobile based health care system [19]. Increase in wireless infrastructure and mobile phone technologies can provide health care to rural people in a faster way. The m-health field promotes a better health care by communicating with the health care professionals located at a longer distance. The advance mobile phone based technology also provides direct voice communication and information transfer capabilities. Hence, advance in technology improves the information access capacity and two-way communication. However, in real time application of m-health care faces many challenges during remote data collection and monitoring of diseases. Remote monitoring and diagnosis of cardiac patient is little difficult in mobile health care. Transmission and storage of large amount of ECG data of a cardiac patent is a big problem in mobile phone based diagnosis of cardiac disorders.

1.10 GSM modem

A global system for mobile communications (GSM) modem is a wireless modem that functions with available 2G networks. A wireless modem is a device which establishes the communication between a PC and wireless network by generating, transmitting and decoding data from a cellular network [22]. A wireless modem behaves like a dial-up modem. The main difference is that a dial-up modem sends and receives data through a fixed telephone line while a wireless modem sends and receives data through radio waves. A GSM modem requires a subscriber identity module (SIM) card to operate, but the modem is controlled by computers through AT-commands. Some standard AT (ATtention)-commands are supported by both GSM modems and dial-up modems. GSM modem also supports few extended sets of AT-commands. The extended AT-commands are defined in the GSM standards which facilitates [23] the following.

- Sending of SMS.
- Writing, reading and deleting of SMS.
- Signal quality monitoring.
- Monitoring of battery charging status.
- Searching,reading and writing of phone book entries.

The writing and sending related AT-commands for SMS messages are given in Table 1.2. The SMS can be received by connecting the modem to a computer. The computer uses

Table 1.2: AT commands used in writing and sending SMS

AT command	Meaning
+CMGS	Send message
+CMSS	Send message from storage
+CMGW	Write message to memory
+CMGD	Delete message
+CMGC	Send command
+CMMS	More messages to send

AT-commands to receive the SMS messages from the modem. The advantage of using

GSM modem for SMS is that the wireless network usually do not charges any fee for receiving incoming SMS. AT-commands related to receive and to read SMS are given in Table 1.3. To send and receive concatenated messages, it is generally recommended to use

Table 1.3: AT commands used in reading and receiving SMS

AT command	Meaning
+CNMI	New message indications
+CMGL	List messages
+CMGR	Read message
+CNMA	New message acknowledgement

GSM/GPRS (general packet radio service) modem with a computer. The concatenated message contains message length more than 160 characters when 7-bit character encoding is used [23].

1.11 Literature survey

The literature survey is done based on different ECG signal application, which are summarized in the following subsections.

1.11.1 On ECG signal compression

ECG is used to measure the electrical activity of the muscle fibers in different parts of the heart. The variations in electrical potentials in 12 different directions are measured and these 12 views of the electrical activity in the heart are normally referred as “leads". A new approach for human identification was presented by Biel *et al.* [24]. An automatic human identification technique was developed to identify a person in many different areas of application. For an example, it can be used in security systems, where authorization check is required. These tests are done with a standard 12-lead rest ECG where selected features are extracted from the ECG to identify a person.

A number of techniques have been reported for efficient transmission of ECG signal over wireless medium [25]. Generally ECG data from a patient usually takes large storage space [5]. It is very difficult to store and transmit this over wireless medium for the purpose of remote patient monitoring. Hence, it becomes essential to compress the data for faster data transmission over bandlimited wireless medium. Compression processes broadly categorized into two basic types like lossless and lossy. There is absolutely no loss of information in lossless compression whereas the compression ratio is low. In case of lossy compression the compression ratio is high while there is a marginal loss of information. In most cases, lossy compression techniques are used for better data compression performance [25]. Lossy compression technique are further classified into three categories i.e., direct data compression, transform domain data compression and parameter based data compression.

A direct data compression algorithm, amplitude zone time epoch coding (AZTEC) was introduced by Cox *et al.* [26] to reduce redundancy in data sequence. This algorithm achieves compression ratio of 10:1. However, the reconstructed signal contains discontinuities and distortion. A direct ECG data compression algorithm, turning point (TP) [27] reduces the sampling frequency of the ECG signal and produces a compression ratio of 2:1. However, the reconstructed signal corresponding to the original signal contains some distortion. A hybrid of AZTEC and TP algorithms, the coordinate reduction time encoding system (CORTES) was developed to reduce the distortion with a compression ratio of 4.8:1 [28]. However, these algorithms cannot be applied to real-time ECG data compression due to the complexity of computation.

A transform domain ECG data compression technique using discrete cosine transform (DCT) was inroduced by Aydin *et al.* [29]. This technique is further improved by using dynamic threshold allocation and variable sub-band coding for enhanced performance [30]. A wavelet packet based algorithm was presented by B. Bradie [31] for the compression of single lead ECG. This algorithm is compared with the karhunen-loeve transform (KLT) technique. The wavelet packet algorithm generated significantly lower data rates with better compression ratio. A two dimensional discrete cosine transform method was presented by Lee and Buckley [32] for compression of ECG data. The 2-D DCT method shows redundancy between adjacent heartbeats and between adjacent samples. Ahmed *et al.* [33] reported that the best performance can be obtained if the signal was decomposed up to the fourth level using non-orthogonal wavelet transform. The technique reported shows higher compression ratio and higher sampling rate. A set partitioning in hierarchical trees (SPIHT) technique was developed by Huang and Miaou [34]. SPIHT is a transform domain data compression technique for mobile tele-cardiology, which uses 3G cellular phone standards. A wavelet transform based international standard, joint photographic expert group (JPEG) was introdued by Bilgin *et al.* [35] for compression of still images. The method uses existing hardware and JPEG2000 software coder and decoder for ECG compression. JPEG2000 codec retains precise rate control and progressive quality of compression.

A parameter extraction technique was presented by Iwata *et al.* [36] for data compression. This algorithm is based on artificial neural network (ANN). A dual three-layered (one hidden layer) neural network system is used for this purpose. The network is tuned up with supervised signals as input signals. The back propagation is used as the learning algorithm. Data compression is accomplished by storing the activation levels instead of the original signal. Szilagyi *et al.* [37], presented a parameter extraction technique for ECG compression. It uses an adaptive entropy coder to obtain 10 times less redundancy than an optimized Huffman coder. Kyoso and Uchiyama presented a microprocessor based transmitter in [38] that reduced ECG data by base line drift canceller, waveform detector and wave analyzer for transmitting the diagnosis information only. An ECG compression algorithm presented by Diaz-Gonzalez *et al.* [39], which uses a max-lloyd quantizer to optimize the low resources of an ECG acquisition and transmission system. This algorithm scheme is based on a first-order differential pulse code modulation (DPCM). The non-uniform quantizer results low distortion in the reconstructed signals due to its low computational complexity. The compression process could be accomplished on-line during the ECG acquisition process. An error effect was reported by Alesanco *et al.* [40] for real-time ECG monitoring in a wireless tele-cardiology application. This technique is based on wavelet compression codec. Both quantitative error and qualitative opinions were presented in order to monitor retrieved information from ECG packets. Nait-Ali *et al.* presented a method for ECG compression in which is based on three major approaches, Time Division Multiplexing (TDM) and multilevel wavelet decomposition followed by parametrical modeling. Pre-processing has been carried out before applying these techniques for detecting and aligning different beats. Lee *et al.* introduces a real-time data compression and transmission algorithm between e-health terminals for a periodic ECG signal in [25]. Transform domain lossy type compression method has been applied to achieve a high compression ratio.

1.11.2 On ECG data transmission over wireless medium

A modelling concept of global system for mobile communications (GSM) based mobile tele-medicine system was presented by R. S. H. Istepanian [41]. This system shows successful multichannel mobile transmission of medical data with low bit error rates. A prototype integrated mobile telemedicine system was introduced by B. Woodward *et al.* [42], which is compatible with existing mobile telecommunications networks. This system will enable a doctor to monitor a patient remotely. A SMS based design presented by R. G. Lee and K. C. Chang [43] consists of a transmitter and a controller for a portable, light weight and small size tele-alarm device. In an emergent situation, when a *heart stroke* occurs, the user only needs to push a button to trigger the controller. The controller automatically sends stored text messages from its database through the transmitter to the specified mobile phone numbers. A new system was presented by S. Borromeo *et al.* [44] for ECG acquisition and wireless transmission purpose. A modular hardware system design based on a field-programmable gate array (FPGA) is also presented for development and debugging purpose. F. Sufi *et al.* [5] presented an ECG compression algorithm, which allows transmission of compressed ECG over bandwidth constrained wireless link through multimedia messaging service (MMS), SMS and hypertext transfer protocol (HTTP). A wide-area wireless ECG transmission technique was presented by A. Alesanco and J. Garcia [45] for real-time cardiac tele-monitoring. The technique uses a new protocol for retransmissions of erroneous packets, which will reduce possible negative effects. M. Kamel *et al.* [46] presented a design of a low cost secure system for data acquisition and visualization in mobile devices. Its design allows easy technological updates and developments. U. Goel *et al.* [47] introduced an application facility to send SMS without the need of an internet service. This application uses a GSM or GPRS modem and a subscriber identity module (SIM) card to send messages to any mobile network. The cost of the message sent is based on the message tariff subscribed with the SIM card. A mobile phone or GSM/GPRS modem is connected to a computer. The instructions called AT(ATtention)-commands are used to control the mobile phone.

1.11.3 On detection of cardiac disorders

An automatic technique for analysis of cardiac abnormal rhythms or cardiac dysrhythmia was presented in [48]. However, this study suggests that automatic dysrhythmia monitoring makes more robust management of dysrhythmia. This technique requires a better processing algorithm for more analysis on the ECG signal. Ozbay *et al.* [49] presented a study on artificial neural networks (ANN) in to classify the ECG arrhythmias. The different structures of ANN have been trained by arrhythmia separately and also by mixing with 10 different arrhythmias. An idea to develop a bio-signal processing tool that can predict possibility of future risk of abnormalities in ECG signals was presented by H. H. Namarvar and A. Vahid. Shahidi [50]. A singular value decomposition analysis of spectral energy distribution in time frequency plane is applied to extract features and cardiac arrhythmias are classified using support vector machines. This method allows an early detection and reduces the risk of cardiac arrhythmias. A real-time continuous arrhythmias detection system (RECAD) was presented by Zhou *et al.* [51], which is based on the wireless sensor network technology. The ambulatory wireless ECG sensor captures and analyzes the patient's ECG signal in real-time. When a cardiac abnormal event is detected, an alarm message is sent to the local access server via local wireless technologies, such as WiFi, bluetooth or digital radio communication. The cardiologist evaluates the received message according to the physical state of the patient. The average cardiac arrhythmia detection rate is found to be 95%. A wireless tele-monitoring system was presented by Ibaida *et al.* [52] to analyse the compressed ECG signal for diagnosis of ventricular tachycardia. This system uses principal component analysis (PCA) for feature extraction and k-mean for clustering of normal and abnormal ECG signals. However, decompression in wireless tele-monitoring causes delay on the doctor's mobile devices. A mobile heart rhythm tele-monitoring system was presented by Mateev *et al.* [53], which evaluates the clinical applicability and patient compliance. This system shows similar results to a standard holter ECG, but the disadvantage is that this system did not provide complete diagnosis.

A computer-based system was presented by Hsia *et al.* [16] for diagnosis of abnormal rhythm and ST-segment in an exercise system. Digitized data are analyzed in a beat-by-beat mode. Each beat is assigned a beat code based on a combination of waveform analysis and RR-interval measurement for abnormal rhythm analysis. Baseline wander is a major problem in exercise ECG which makes accurate reading extremely difficult. This system provides accurate ST-level and slope measurements but it requires more computation time. K. Wang [54] presented a method for recognizing the shape of ST-segments. This method is based on the approximation that ST-segment is either a line segment or a parabolic segment. The estimation of ST-segment endpoint is very much difficult which causes implementation of the method practically impossible. Maglaveras *et al.* [55] presented an automatic ischemic episodes detection algorithm, which is based on a supervised neural network. The performance of ischemic episodes resulting from ST-segment elevation or depression are measured using the European ST-T database. This neural network (NN) based algorithm implementation provides fast and reliable detection of ischemic episodes whereas training of the neural network is time consuming. An algorithm based on nonlinear principal component analysis was presented by Stamkopoulos *et al.* [56] for detection of ischemic episodes. The feature extraction method is nonlinear and it is implemented using a multilayered neural network. Garcia *et al.* [57] presented a new detector to determine changes in the repolarization phase (ST-T complex) of the cardiac cycle. The advantage of this detector is that it finds both ST-segment deviations and entire ST-T complex changes. A new myocardial ischemia indicator presented by Lemire *et al.* [58], which examines the information content of a combined ST-segment and T-wave complete morphology through fast wavelet transform (FWT) and Shannon's entropy. An automatic algorithm was presented by A. Smrdel and F. Jager [59] for detection of time varying episodes of ST-segment. The algorithm tracks the ST-segment reference level to detect the changes in ST-episodes. F. Jager *et al.* [60] developed an automatic system to detect transient ST-segment in ECGs. The work was challenging and realistic research resource for development. Exarchos *et al.* [61] presented an automated methodology, which is based on association rules for the detection of ischemic beats in long duration electrocardiographic recordings. A limitation of the methodology is that it requires a representative training set in order to extract reliable rules. An automatic technique for detection of ST-segment deviation was presented by Afsarl *et al.* [62] to diagnose the coronary heart disease (CHD). The lead-dependent karhunen-loeve transform (KLT) bases are applied to reduce the ST-segment data. Faganeli *et al.* [63] reported that ischemia is presented by transient ST-segment episodes. It occurs due to increase in heart rate. An automated system for on-line monitoring and detection of ST-changes was presented by Mohebbi *et al.* [64]. In this system a normal beat template is used as reference. A set of rules based on ST-slope or ST-deviation measurements are defined by cardiologists for detection of ischemic beats. A window classification is used for detection of ischemic beat sequences. The performance of the system results a high sensitivity and good positive predictivity. Its main advantages are short processing time and acceptable accuracy.

1.12 Objectives of the Thesis

Aim of the thesis is to develop the algorithms for establishing an efficient and faster transmission of ECG signal to a health care centre or hospital over wireless medium and to develop an automatic cardiac abnormalities detection technique from compressed ECG signal. At health care center, the received compressed ECG signal is utilized to detect cardiac disorders like bradycardia, tachycardia and ischemia. The specific objectives of the thesis work are as follows:

- Development of an automatic ECG signal compression technique based on empirical mode decomposition (EMD). EMD based approach is a data adaptive process which allows an iterative decomposition of the signal into a series of functions known as intrinsic mode functions (IMFs). It is convenient to analyze nonlinear and non-stationary data at instantaneous frequency (IF).

- To develop an algorithm for transmission of compressed ECG data and to reconstruct the ECG signal from the received compressed data. A GSM modem with SIM card communicates PC using AT-commands to transmit compressed ECG in the form of SMS which is a cost effective off-line process. The received SMS messages are transferred to PC using blue-tooth and the data decompression processes are carried out to reconstruct the ECG signal.

- Development of an algorithm for detection of i) abnormal heart rhythm like bradycardia and tachycardia through HR calculation from decompressed ECG signal and ii) ischemic episodes using European ST-T database through the measurement of ST-segment deviation as well as T-wave amplitude changes relative to isoelectric line.

1.13 Thesis Organization

Thesis is organized as follows.

- Chapter 1 introduces anatomy of the human heart, importance of ECG signal and standard ECG databases. Different types of cardiovascular disorders are also presented in this chapter. The generation of ECG signal from electrical activity of heart muscles is also presented. This chapter also introduces mobile health care system and the facilities to use wireless modems. The literature studies on ECG signal compression, wireless ECG data transmission and detection of cardiac disorders are described in this chapter.
- Chapter 2 elaborates the necessity of ECG signal compression. Theoretical background of empirical mode decomposition (EMD) technique is also described in this chapter. The proposed methodologies for ECG signal compression and decompression are also presented in this chapter.
- Chapter 3 explains about the transmission of the compressed ECG data over wireless medium. This chapter also describes the SMS based efficient transmission of the compressed ECG. The techniques used to reconstruct the original from the received text SMS messages are also presented in this chapter.
- Chapter 4 presents the proposed algorithm for detection of cardiac disorders. The methodologies for detection of heart dysrhythmia abnormalities (like bradycardia and tachycardia) and ischemic episodes are also described in this chapter.
- Chapter 5 concludes the whole work and also discusses the scope of future work.

CHAPTER 2

ECG SIGNAL COMPRESSION AND DECOMPRESSION

2.1 Introduction

The electrocardiogram (ECG) is a graphical recording of the electrical signals generated from the heart [1]. ECG is used as a diagnostic tool for cardiac patient monitoring and diagnosis of heart disorders. ECG provides valuable diagnostic information about functioning of heart and cardiovascular system. A patient located at a rural cardiac diagnostic center faces lots of difficulties in getting appropriate treatment due to unavailability of advance equipments and specialist doctors. In computer based technology, faster and efficient diagnosis makes a big difference in saving a patient's life. ECG data from a cardiac patient in a real time monitoring process can grow up to 2.77 GB in one day [5]. Storage and transmission of such a large amount of data is very difficult in real time applications using wireless communication technology. It is also very much difficult for rural patients to get faster diagnosis from expert doctors available in developed cities. Hence, it becomes essential to compress the ECG data for establishing faster diagnosis through wireless medium.

Several algorithms [26–29,31,33,37,65] have been developed for compression of ECG signal. The lossless compression [66–68] preserves all information, while the compression ratio is low. In case of lossy compression the compression ratio is high in expense of marginal loss of information. In the field of information technology lossy compression methods are used to represent the information content. Lossy compression technique reduces the amount of data needed to store or transmit by removing redundant and unnecessary information. Lossy ECG compression methods have been presented in [69–71]. It has been shown in previous work [72], that lossy compression of ECG signal results in information loss within the acceptable limit. This marginal loss of information hardly affects important morphological features of ECG signal. In this work, a lossy compression scheme is adapted for remote patient monitoring.

In most cases, lossy compression techniques are used for better data compression performance compared to lossless encoding techniques [25]. Moreover, for remote health care systems, the ECG data need to be compressed sufficiently so that easy transmission of data is possible over wireless medium. Several wireless transmission based on lossy compression [42, 43, 45–47, 73] techniques have been developed for remote patient monitoring. The aim of the compression technique is to attain maximum data reduction and to preserve the significant signal features.

2.2 Types of compression

ECG data needs to be compressed for efficient data storage and faster transmission over wireless medium. Data compression is the process of eliminating redundant information so as to attain maximum data volume reduction and preserve important information on reconstruction. The size of data reduces considerably by compression which makes memory space available for easy storage of digitized ECG in a storage device. Particularly in tele-health care (i.e., tele-cardiology) purpose, ECG data need to be transmitted efficiently so that the proper diagnosis can be made by cardiac specialists located away from the remote health centers. Thus, main goal of ECG data compression is easy storage and faster transmission over long distance. Compression processes broadly categorized into two basic types i.e., lossless and lossy.

2.2.1 Lossless techniques

The original data can be exactly retrieved from their compressed form if data are compressed using lossless techniques. There is absolutely no loss of information in lossless technique [74]. There are many situations like text compression, radiological image compression, etc., where, it is required that reconstructed data to be identical to the original. Hence, lossless compression techniques are suitable for this purpose. An important area for application of lossless technique is compression of text data. The lossless technique such as Huffman coding is widely used for compressing textual data [75]. The lossless compression [66–68] preserves all information, while the compression ratio is low. There are situations where lossy compression is used to get more data compression.

2.2.2 Lossy techniques

The unnecessary or redundant information are eliminated by focusing more on saving space over preserving the accuracy of the data. In lossy compression, only an approximation of the original data can be retrieved. In most cases, lossy compression techniques are used for better data compression performance as compared to lossless encoding techniques [25]. Hence, the lossy compression techniques are suitable for remote patient monitoring. The techniques used in ECG compression evaluates the compression efficiency in terms of compression ratio (CR) [28] and percent root mean square difference (PRD) [27]. The CR is defined as ratio of original data input to the compressed output data. The PRD is the error difference between original signal before compression and reconstructed signal. As stated in [25], lossy compression technique for ECG data are further classified into three categories.

- Direct data compression
- Transform domain data compression
- Parameter extraction based data compression

2.2.2.1 Direct data compression

The direct data compression techniques attempts to reduce redundancy in data sequence by examining a successive number of neighboring samples both previous and future. Commonly used direct data compression methods are amplitude zone time epoch coding (AZTEC) [26, 76], turning point (TP) [27], coordinate reduction time encoding system (CORTES) [28] and the Fan [77].

2.2.2.2 Transform domain data compression

In the transform domain techniques, redundancy is reduced by applying linear transformation to the signal and then compression is applied in the transform domain instead of time domain. It transforms the original data into a domain that more accurately reflects the information content. The reconstruction of the signal is done by inverse transformation with a certain percentage of error. The transform domain method converts the time domain signal to frequency domain or other domains [25]. For an example, the transform domain techniques includes Fourier transform, Fourier descriptor [78], Karhunen Loeve transform (KLT) [65], the Walsh transform, discrete cosine transform (DCT) [79] and wavelet transform [80].

2.2.2.3 Parameter extraction based data compression

In the parameter extraction technique, the extraction of a set of useful parameter from the original signal is carried out and the same are used in the reconstruction process [81]. Some of the methods includes namely peak-picking, neural network method and parameter extraction method [37]. The peak picking compression technique presented in [82] is based on the sampling of a continuous signal at maxima and minima. The extraction of signal parameters carry the information about the signals. Nowadays, artificial neural networks (ANN) are used for pattern recognition and classification problems. The important features of ANN based techniques exhibit adaptation or learning. For example, using ANN for ECG compression, Iwata *et al.* [36] presented a data compression algorithm for holter recording with ANN. A dual three-layered neural network system is used for this purpose. The back propagation algorithm is used as the learning technique.

In general, lossy compression technique uses transform coding to get highly compressed data. It transforms the original data into a domain that more accurately reflects the information content. The most suitable transform domain compression technique is wavelet transform, which allows the analysis of non-stationary signal. However wavelet based analysis faces difficulties like uniformly poor resolution due to limited size of the basic wavelet function and its nonadaptive nature. The limited length of the basic wavelet function makes the quantitative definition of the energy-frequency-time distribution difficult [83]. Sometimes, the interpretation of the wavelet can also be counter intuitive for ECG signal analysis. Wavelet transform is having better frequency resolution and poor time resolution for low frequencies and vice versa for high frequencies [84]. For example, if a change of the ECG signal is occurred locally, it is required to look the result in the high-frequency range of the signal. To define the local events in low frequency range of the ECG signal still it is required to look for its effect in high frequency range of the signal [83]. Such interpretation will be difficult to analyze an ECG signal from a wavelet based method. Another difficulty of the wavelet analysis is its non-adaptive nature i.e. once the basic wavelet is selected, one will have to use it to analyze all the data. A data adaptive technique is applied in this thesis to overcome the difficulties [83]. This technique is based on empirical mode decomposition (EMD) [85], which analyses the non-stationary signal in detail.

2.3 Empirical Mode Decomposition

A data adaptive method to analyse non-stationary signal is based on empirical mode decomposition (EMD) [85]. In EMD the bases are derived from the multivariate data which are nonlinear and non-stationary. Time-frequency analysis of nonlinear and non-stationary data requires a multi scale approach at the accuracy level of instantaneous frequency (IF). Hilbert transform (HT) is convenient to analyze nonlinear and non-stationary data at IF. Some standard transform methods are not suitable for analysis of nonlinear and non-stationary data due to certain limitations like:

- Fourier and wavelet approach employs predefined basis functions (harmonic, mother wavelet) which are fixed bases.
- In time-frequency analysis, the accuracy depends on data length and stationary patterns, which are short and irregular. The integral transforms representation makes trade-off in frequency resolution.
- Standard patterns in data occur at their own intrinsic scales and thus provides inadequate measurement.

The advantages of data driven approach, EMD is that the components are derived empirically from the data and holds the properties like,

- Data-adaptive, which facilitates the intrinsic patterns at multiple scales, while not requiring the rigid assumptions of harmonic or stationary data.
- Enhanced accuracy, which predicts the time frequency accuracy at the IF level and a natural account of nonlinearity.
- The integrity of multivariate bases which facilitates synchronization, causality and data association.

The EMD based aproach allows an iterative decomposition of the signal into a series of functions known as intrinsic mode functions (IMFs). Theoretically, each intrinsic mode function (IMF) which is a simple oscillatory component extracted from original signal, contains all frequency from highest to lowest. IMFs are obtained from the signal by means of sifting process [83]. As reported in Huang *et al.* [83], an IMF is a function which must satisfy two conditions: (a) the number of extrema must either be equal to or at most differ by one from the number of zero crossings. (b) the mean values of both the envelope defined by the local maxima and the envelope defined by the local minima are zero at any point in the data. For an example, assume that a temporal continuous time signal is $x(t)$. The sifting process [83] applied to $x(t)$ consists of various processes which are represented as per [86].

1. Find the location of all the extrema (both maxima and minima) of $x(t)$.
2. Interpolate (cubic spline fitting) between all the maxima extrema ending up with entire upper envelope $x_{max}(t)$.
3. Interpolate (cubic spline fitting) between all the minima extrema ending up with entire lower envelope $x_{min}(t)$.
4. Compute the mean envelope between upper envelope and lower envelope $m(t) = \frac{x_{max}(t)+x_{min}(t)}{2}$.
5. The IMFs are calculated using number of iterations. The difference between the data $x(t)$ and the mean $m(t)$ is the first component of IMF which is given as $h_1(t) = x(t) - m(t)$. The component $h_1(t)$ is an IMF, if it satisfies the conditions of IMF otherwise it is calculated iteratively with stopping criteria. If IMF criteria is not satisfied, $h_1(t)$ is treated as the data input to the second sifting (iterative) process. The second component is the difference between the data $h_1(t)$ and the mean $m_{11}(t)$ that is $h_{11}(t) = h_1(t) - m_{11}(t)$. The sifting process is repeated 'k' times until $h_{1k}(t)$ is an IMF, that is $h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t)$. A stopping criterion is employed to the number of sifting iterations which is obtained by limiting the size of the standard deviation (SD), computed from the two consecutive sifting results. $SD = \sum[\frac{|h_{1(k-1)}(t)-h_{1k}(t)|^2}{h^2_{1(k-1)}(t)}]$. Here SD is predefined to be very small and iterative calculations are carried out so long as the stopping criteria is not met. The residue is calculated as $r_1(t) = x(t) - h_{1k}(t)$.
6. After the IMF is found the residue is calculated as $r_v(t) = r_{(v-1)}(t) - h_{(v-1)}(t)$, for v is 2, 3, 4, ..., M.

   $r_v(t)$ is the data that should be treated as input at the calculation of v^{th} IMF. Clearly if $v = 1$ for IMF 1, then $r_1(t) = r_{(0)}(t) - h_{(0)}(t)$, where, $r_0(t) = x(t)$ and $h_0(t) = m_1(t)$

7. For calculation of ‘M’ number of IMFs, step 1 to 6 is repeated.

If ‘M’ rounds of sifting process is performed on the given signal $x(t)$, it will be decomposed to a set of ‘M’ IMFs and a residue signal which can be denoted as

$$x(t) = \sum_{k=1}^{M} h_k(t) + r_v(t)$$

The above equation shows that a signal which is decomposed by EMD can be reconstructed easily by simple addition of the IMF components $h_k(t)$ and the residue signal $r_v(t)$.

2.4 Proposed Framework

2.4.1 Compression

The methodology followed for ECG data compression consists of following stages: signal decomposition through empirical mode decomposition (EMD), downsampling, discrete cosine transform (DCT), window filtering and Huffman encoding. The work flow diagram for the signal compression process is shown in Figure 2.1. All the stages are explained as follows.

2.4.1.1 EMD based signal decomposition

The ECG signal is decomposed into a series of IMFs using EMD technique. The last IMF is called the residue. As an example Figure 2.2 represents the EMD decomposition of the ECG signal taken from European ST-T ECG record tape no. # e0613. It contains sixteen IMFs and one residue. Out of 16 IMFs, first two IMFs (i.e., IMF 1 and IMF 2) are removed as these are high frequency noise components. Therefore, by removing first two IMFs, mostly noise components of the signal are removed. The remaining IMFs including the residue signal are further processed in the next stage.

2.4.1.2 Downsampling

The common idea of downsampling is to reduce the cost of processing. Generally, memory required to implement a signal processing system is proportional to the sampling

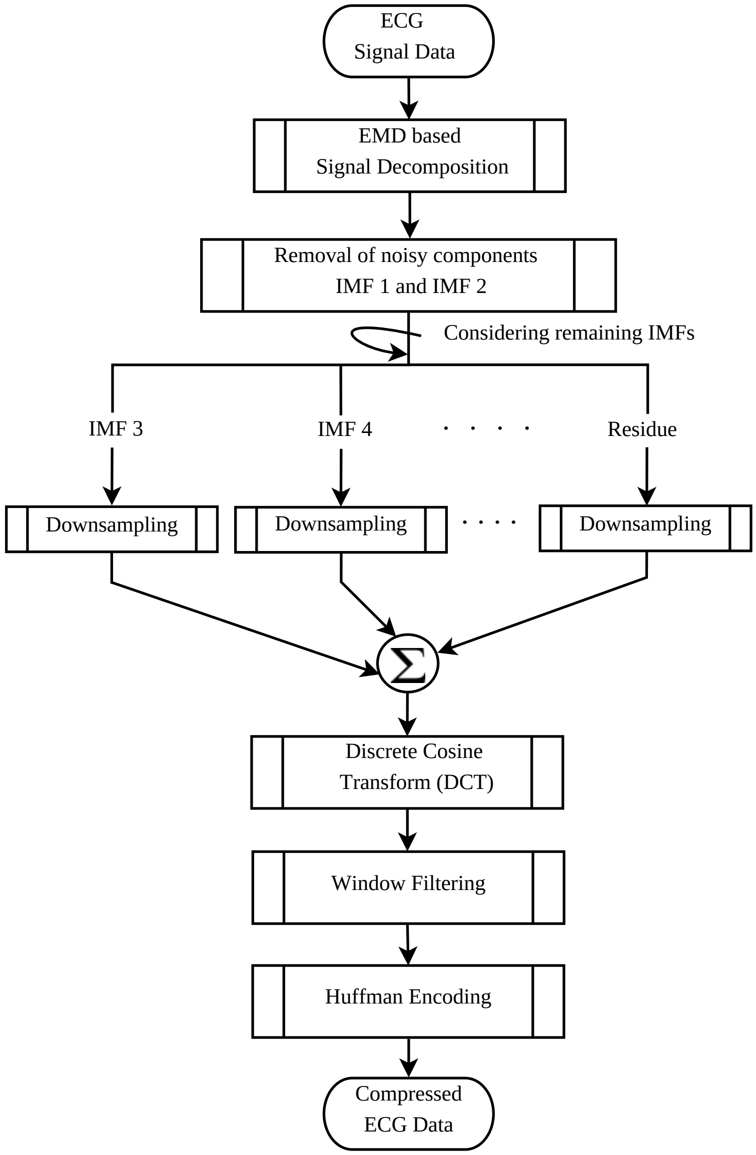

Figure 2.1: Work flow diagram for ECG signal compression

rate. The down sampled data can be used as an input to a device which is operating at a low sampling rate. The downsampling factor (D) is obtained using the minimum distance between extrema points in the first IMF (i.e., IMF 1) [86]. The equation to calculate down sampling factor is given as $D = \frac{E_{min}}{2}$, where E_{min}, is the minimum distance between two consecutive extrema points in IMF 1. The downsampled factor is found to be '2'. Thus half downsampling is applied to the all IMFs excluding the first two noisy IMFs (i.e., IMF 1 and IMF 2). The downsampled signals are summed up and

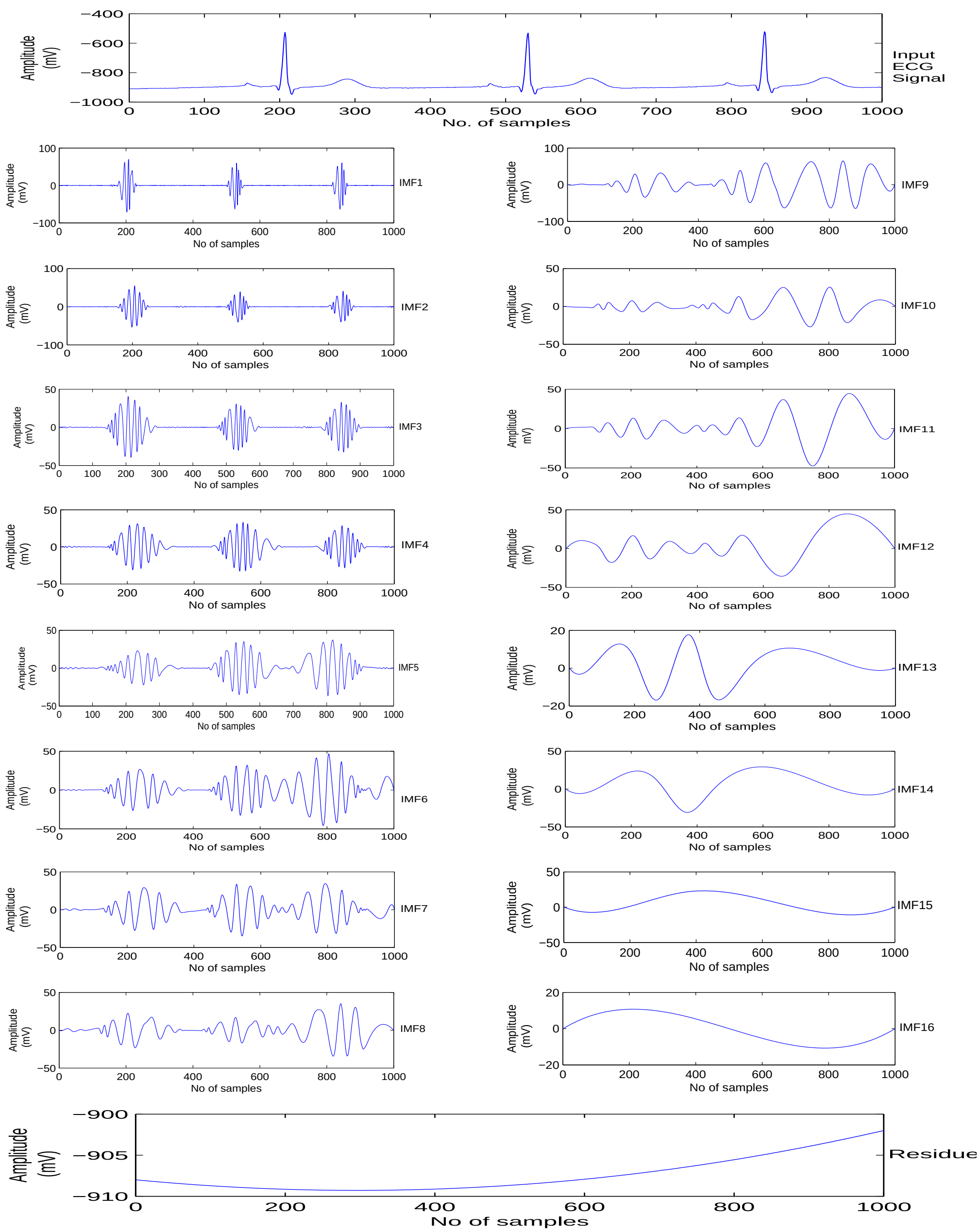

Figure 2.2: Decomposition of input ECG signal (European ST-T record no. # e0613)

fed as input to the next stage.

2.4.1.3 Discrete Cosine Transform (DCT)

DCT is a transform based ECG compression methods compression method which uses orthogonal transform to the signal [87]. It is used to reduce the redundancy present in the signal. DCT is generally used for data compression due to its greater ability to concentrate the signal energy in few transform coefficients. Only a few coefficients contain information about the real signal while others appear as less important details [87]. The real DCT coefficient makes it simpler for efficient implementation. DCT expresses the signal in terms of sum of cosine functions with different frequencies and amplitudes. The frequency domain signal is represented as forward DCT, $C(k)$. The DCT of a signal $x(n)$ of length N is defined by

$$C(k) = \alpha(k) \sum_{n=0}^{N-1} x(n) cos \frac{2\pi}{N}(n + \frac{1}{2})k, \tag{2.1}$$

$$k = 0, 1, 2, ..., (N - 1),$$

$$n = 0, 1, 2, ..., (N - 1).$$

where, $C(k)$ is the k^{th} DCT coefficient and the scale factor $\alpha(k)$ is defined as

$$\alpha(k) = \begin{cases} \sqrt{\frac{1}{N}} & for \ \ k = 0 \\ \sqrt{\frac{2}{N}} & for \ \ k \neq 0 \end{cases}$$

DCT operates on a function at a finite number of discrete data points [88] and DCT is applied because of following characteristics: (i) it maintains the periodicity of an ECG signal. (ii) it enables high compression rate during Huffman coding [25]. (iii) it provides high de-correlation and energy compaction property [89].

2.4.1.4 Window Filtering

In this application, windowing is used for decomposing the long duration signals into shorter duration. The characterstics of the signal remains stationary over short duration of window [90]. Furthermore, the occurrence of false discontinuities at the edges of the signals are eliminated. A rectangular window function is applied to the discrete cosine transformed signal which modifies the discontinuities at the edges [91]. For an example, the size of the window is chosen to accommodate 1000 samples. The signal is sampled at 250Hz, it means 4 sec data is available for a particular window. The signal after compression can be transmited for cardiac disorder detection. As the RR-interval duration varies from 600-1200ms, it can be ensured that the signal of 1000 samples can cover all the information for detection of cardiac dysrhythmia.

2.4.1.5 Huffman encoding

The final step for the ECG compression algorithm is Huffman or variable length coding. Huffman coding is based on frequency of occurance of data points in a data stream [75]. The principle is to allocate minimum number of bits to a datum that appears more frequently. Huffman code can be briefly summarized as follows.

1. Initialization: Put all distinct data points of a data stream in a list and sort them in ascending order. Each distinct datum is called a node.
2. Repeat the following steps until list has only one node left.

   a. From the list pick two nodes having lowest frequency and create one parent node of them.

   b. Assign the sum of children's frequency to the parent node and insert it into the list. This create a tree like structure.

   c. Assign 0, 1 to the two branches of tree and delete the children from the list.

Huffman code can reduce the redundant information with a group of codes. It provides an optimal coding length in terms of average value of bits per sample as well as it reduces cost of encoding. The method is that a binary code is assigned to the data whose length is variable. The basic idea is to assign fewer bits (i.e. codewords) to frequently occurring data (those having higher probabilities) and more bits to less occurring data (those having lower probabilities) [75]. The compressed ECG signal is encoded as text for transmission over wireless networks.

2.4.2 Decompression

The signal can be reconstructed from the compressed data by applying decompression procedure. The reconstruction process is in the reverse order of compression methods, which are explained below. The work flow diagram for reconstruction of ECG signal is shown in Figure 2.3.

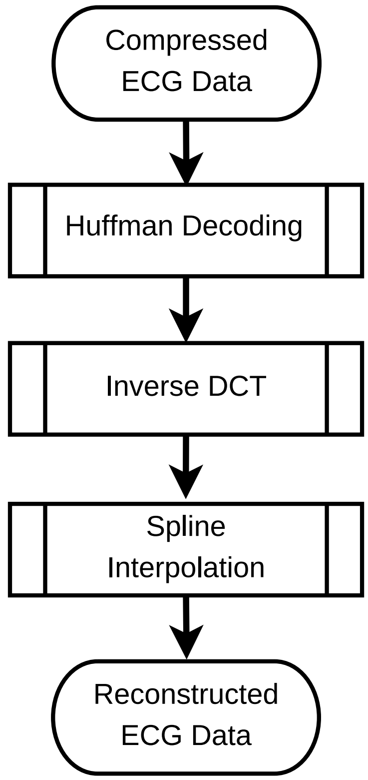

Figure 2.3: Work flow diagram for ECG signal reconstruction

2.4.2.1 Huffman decoding

The Huffman decoding or inverse Huffman coding is the reverse process of Huffman encoding. In the process of Huffman encoding a Huffman tree is generated with a root and its leaves. The Huffman tree is helpful while decoding the encoded data. In decoding, Huffman-encoded file has to be read starting with the first bit in the stream and then uses successive bits from the stream to determine whether to go left or right [75]. When a leaf is reached, a character is decoded and placed on the output of the stream. The next bit in the input stream is the first bit of next character. Again same procedure is followed until each character in the stream is decoded. The amount of decoded data may contain only the important information which will be carried by the DCT coefficients.

2.4.2.2 Inverse Discrete Cosine Transform (IDCT)

Signal can be reconstructed accurately from only few DCT coefficients those carries important information about the signal. The time domain signal $x(n)$ can be reconstructed from forward DCT signal, $C(k)$ by using IDCT. The time domain signal reconstructed contains less number of samples for the specified window length. The number of samples can be increased for accurate reconstruction of the required signal by using more number of data points. The discrete time signal $x(n)$ can be given by IDCT.

$$x(n) = \sum_{k=0}^{N-1} \alpha(k)\ C(k) cos \frac{2\pi}{N}(n + \frac{1}{2})k, \tag{2.2}$$

$$n = 0, 1, 2, ..., (N - 1),$$

$$k = 0, 1, 2, ..., (N - 1).$$

where, $C(k)$ and $\alpha(k)$ are the parameters as defined in previous section.

2.4.2.3 Spline Interpolation

The data received are upsampled using spline interpolation method to get uniform sampled data. This process uses the cubic spline interpolation to reconstruct the original signal [25]. The cubic spline method provides less distortion which in turn reconstruct a smooth signal. The cubic splines are most desirable interpolation scheme because other lower order interpolation scheme like linear or quadratic can cause errors in estimation of the maxima and minima [92]. Using this interpolation scheme the required ECG signal is reconstructed effectively. Spline interpolation is to draw smooth curves through a number of points. The spline consist of weights attached to a flat surface at the points to be connected. The points are numerical data. The weights are the co-efficient on the cubic polynomials used to interpolate the data. These co-efficients bend the line so that it passes through each of the data points without any erratic behavior or breaks in continuity [93]. The idea is to fit a piecewise function of the form,

$$S(x) = \begin{cases} s_1(x) & \text{if } x_1 < x < x_2 \\ s_2(x) & \text{if } x_2 < x < x_3 \\ \vdots & \\ s_{n-1}(x) & \text{if } x_{n-1} < x < x_n \end{cases}$$

where s_i is a third degree polynomial defined by

$s_i(x) = a_i(x - x_i)^3 + b_i(x - x_i)^2 + c_i(x - x_i) + d_i, \quad$ for $i = 1, 2, 3, \ldots, n-1$.

$S(x)$, $S'(x)$ and $S''(x)$ should precisely continuous over x_1 to x_n. The coefficients are given by

$a_i = \frac{M_{i+1} - M_i}{6h}$

$b_i = \frac{M_i}{2}$

$c_i = \frac{y_{i+1} - y_i}{h} - (\frac{M_{i+1} + 2M_i}{6})h$

$d_i = y_i$ where $y_i = S(x_i)$, $M_i = s_i'(x_i)$ *and* $h = x_i - x_{i-1}$.

The resulted spline interpolated signal is the reconstructed ECG. The stepwise output signals of the decompression process are shown in Figure 2.4.

2.5 Experimental Results and Discussions

The proposed EMD based compression algorithm is evaluated using European ST-T database [6]. The compression ratio (CR) and percent RMS difference (PRD) for different ECG signals of European ST-T data base using the proposed method are given in Table 2.1. The CR is defined as,

$$CR = \frac{N_{inp}}{N_{out}} \tag{2.3}$$

where, N_{inp} is the size of original signal and N_{out} is the size of compressed signal. The average CR and PRD for selected ECG signals is found to be 23.5:1 and 1.38 respectively. For comparison purpose, the proposed EMD based compression algorithm is evaluated by using MIT-BIH arrhythmia database [7].

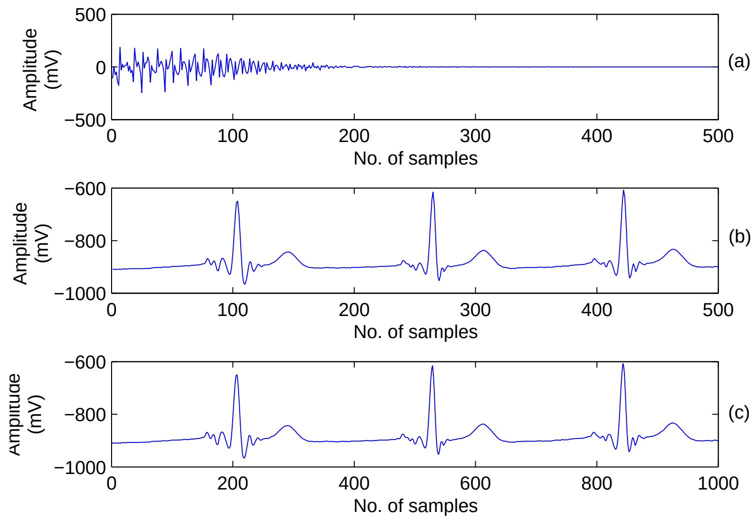

Figure 2.4: Signals at different stages of ECG signal reconstruction

(a) Huffman decoded Signal (b) Signal after IDCT (c) Reconstructed ECG

The MIT-BIH arrhythmia database is used to conduct research on arrhythmia analysis. This database is put together by Massachusetts Institute of Technology (MIT) and Beth Israel Hospital (BIH). In 1980, this database was the first generally available set of standard test material for evaluation of arrhythmia detectors and also for basic research into cardiac dynamics. The MIT-BIH arrhythmia database contains 48 half-hour selec-

Table 2.1: Evaluation of CR and PRD for European ST-T database

ECG Record	CR	PRD
e0105	23.26	0.71
e0112	23.28	6.92
e0122	23.81	0.384
e0127	23.26	0.56
e0207	23.28	4.22
e0211	23.26	2.31
e0404	23.83	0.1
e0417	23.82	0.243
e0606	23.27	0.13
e0613	23.29	0.22
e0615	23.81	0.46
e0704	23.82	0.24

tions of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH arrhythmia laboratory between 1975 and 1979 [7]. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. Each beat in these records are properly annotated by a set of expert cardiologists.

The performance of the proposed method is evaluated using CR and percent RMS difference (PRD) values. The CR values are obtained as per the equation 2.3. The PRD is represented to evaluate the reconstruction efficiency. The signal after decompression is compared with the original signal and the PRD is expressed as,

$$PRD(\%) = \sqrt{\frac{\sum_{n=0}^{N-1}(x_s(n) - x_r(n))^2}{\sum_{n=0}^{N-1} x_s(n)^2}} \times 100 \tag{2.4}$$

where, $x_s(n)$ is the original signal before compression, $x_r(n)$ is the reconstructed signal and N is the total number of data instances. The experimental values of CR and PRD using MIT-BIH arrhythmia database [7] are given in Table 2.2. The average CR and PRD are found to be 23.74:1 and 1.49, respectively. The evaluation parameters CR and PRD are also compared with the result presented by other researchers for the ECG record no. # 117. In comparison to earlier direct time-domain lossy compression techniques [26–28, 77], the proposed transform domain lossy compression technique shows high CR and low PRD values. In comparison to existing lossy transform domain techniques [25, 80], the result obtained by the proposed technique shows high CR value and comparable PRD values. The proposed lossy compression technique provides high CR value as redundant and irrelevant information are removed in each stage by applying a series of compression methods. In this method, though signal is compressed by removing first two IMFs but information loss is very less. In other stages of signal compression, there is also marginal loss of information occurs. In last stage, Huffman encoding is used so that no loss of information occurs. Therefore overall CR value is high and the PRD values are comparable with earlier reported techniques [25,80]. The comparison performance of the proposed algorithm with other existing state-of- the-art techniques for the ECG record

Table 2.2: Performance of proposed compression algorithm

ECG Record	CR	PRD	ECG Record	CR	PRD
100	24.11	1.31	201	23.81	0.72
101	23.26	0.87	202	23.73	0.49
102	23.81	1.07	203	23.26	1.88
103	23.28	2.38	205	23.81	1.60
104	23.85	1.12	207	23.65	0.59
105	23.82	0.48	208	23.28	2.57
106	23.81	1.90	209	23.63	1.87
107	23.27	1.90	210	23.74	0.29
108	24.39	0.32	212	23.26	1.43
109	23.89	0.56	213	23.57	3.07
111	24.15	0.65	214	23.81	1.22
112	23.87	0.73	215	23.83	1.38
113	23.81	2.53	217	23.91	0.89
114	25.00	0.86	219	23.26	2.00
115	23.43	2.87	220	23.43	3.38
116	23.56	3.84	221	23.51	1.14
117	24.46	1.72	222	23.83	1.00
118	23.85	2.90	223	23.62	0.95
119	23.81	1.71	228	26.81	0.54
121	23.83	0.18	230	23.29	2.01
122	23.96	0.99	231	23.85	2.20
123	24.10	2.37	232	23.82	0.91
124	23.26	1.65	233	23.98	2.44
200	23.81	0.86	234	23.27	1.41

no. # 117 is presented in Table 2.3. The proposed compression method is also compared with other algorithms presented by other researchers for the ECG record no. # 100, # 117 and # 119. The comparison details are given in Table 2.4. The algorithms presented

Table 2.3: Other algorithms comparison with proposed method for ECG record 117.

Compression Algorithm	CR	PRD
AZTEC [26]	10	28
TP [27]	2	5.3
CORTES [28]	4.8	7
Fan [77]	3	4
SPHIT [80]	8	1.18
S. Lee *et al.* [25]	24.4	1.17
Proposed Algorithm	**24.46**	**1.72**

Table 2.4: Performance comparison of different type ECG compression schemes

Algorithm	ECG Record 100		ECG Record 117		ECG Record 119	
	CR	PRD	CR	PRD	CR	PRD
Lee *et al.* [32]	24	8.1	10	2.96	12	5.7
Tai *et al.* [94]	10	1.48	10	0.67	20	2.17
Chou *et al.* [95]	24	4.06	10	0.98	10	1.03
Eddie B.L *et al.* [96]	24	3.95	10	0.86	10	0.93
S. Lee *et al.* [25]	23	1.94	24.4	1.17	19.3	2.05
Proposed Algorithm	**24.11**	**1.31**	**24.46**	**1.72**	**23.81**	**1.71**

by [25, 32, 94–96] for the ECG record no. # 100 reports the values of CRs 24:1, 23:1, 24:1, 24:1 and 10:1, respectively with corresponding PRDs 8.1, 1.94, 4.06, 3.95 and 1.48. The proposed algorithm for the same record shows the CR value of 24.11:1 and PRD value 1.31. The proposed technique shows better PRD value with a high value of CR. The PRD value is very low which shows better result for exact reconstruction. Similarly for the ECG record no. # 117 the algorithms presented by [25, 32, 94–96] reports CRs values of 10:1, 24.4:1, 10:1, 10:1 and 10:1, respectively with corresponding PRDs of 2.96, 1.17, 0.98, 0.86 and 0.67. The proposed algorithm for the same record shows the CR value of 24.46:1 and PRD value 1.72. Hence the proposed method presents high CR value and comparable PRD value. The proposed technique is also compared with the algorithms reported in [25, 32, 94–96] for the ECG record no. # 119, which shows the values of CRs are 12:1, 19.3:1, 10:1, 10:1 and 20:1 respectively with corresponding PRDs 5.7, 2.05, 1.03, 0.93 and 2.17. The proposed algorithm shows the CR value of 23.81:1 and PRD value 1.71 for the same ECG record. Similarly, the proposed compression method is also compared with reported technique in [97] for the ECG record no. # 101, # 119, # 210 and # 232. The comparison details are given in Table 2.5.

For ECG record no. # 101, # 119, # 210 and # 232 the reported technique in [97] shows the values of CRs as 26.7:1, 23:1, 11.55:1 and 4.31:1 respectively and PRDs as 1.77, 1.95, 0.49 and 0.25 respectively. For same ECG records the proposed algorithm yields the values of CRs as 23.26:1, 25.12:1, 23.74:1 and 23.82:1 and PRDs as 0.87, 1.7, 0.29 and 0.91 respectively. From these comparisons it is seen that except few records, the proposed

Table 2.5: Performance comparison of proposed method with Zahhad *et al.* method

ECG Record	Zahhad *et al.* [97] method		**Proposed Algorithm**	
	CR	PRD	CR	PRD
101	26.7	1.77	**25.63**	**0.85**
119	23	1.95	**25.12**	**1.7**
210	11.55	0.49	**23.26**	**0.29**
232	4.31	0.25	**23.81**	**0.19**

technique shows improved CR and PRD values as empirical mode decomposition (EMD) based method data adaptive [85].

The proposed EMD based compression technique is also applied to real ECG signal databases which are recorded from five volunteers using ADInstruments Power lab 26T ECG machine and Labchart Pro software with 400 Hz and 1000 Hz sampling frequency. The data is not associated with any particular age group. Experimental results shows the values of CR and PRD as given in Table 2.6 and Table 2.7. The average CR and PRD are found to be 23.29:1 and 0.88, respectively for the ECG records shown in Table 2.6 whereas for ECG records of Table 2.7 the average CR and PRD are found to be 25.49:1 and 0.97 respectively.

Table 2.6: Performance evaluation of real time ECG signals recorded at 400Hz

Real ECG Record	CR	PRD
Volunteer 1	17.86	0.66
Volunteer 2	23.26	0.99
Volunteer 3	18.18	1.12
Volunteer 4	28.57	0.57
Volunteer 5	28.57	1.08

Table 2.7: Performance evaluation of real time ECG signals recorded at 1000Hz

Real ECG Record	CR	PRD
Volunteer 1	25.69	1.07
Volunteer 2	28.57	0.83
Volunteer 3	30.3	0.53
Volunteer 4	24.39	1.24
Volunteer 5	18.52	1.18

The proposed EMD based compression technique decomposes the signal into a series of IMFs. The first two IMFs (mostly noise components) are removed to get highly compressed data. The removal of redundant and irrelevant information in each stage further increases the CR values. Though there is marginal loss of information in each stage but Huffman encoding preserves all the information without any data loss. The Huffman coded compressed data upon reconstruction provides the PRD values which are comparable with earlier reported methods.

2.6 Summary

This chapter presents a new technique for ECG signal compression based on empirical mode decomposition (EMD). First, EMD technique is applied on ECG signal to decompose it in several intrinsic mode functions (IMFs). Next, downsampling, discrete cosine transform (DCT), window filtering and Huffman encoding techniques are used sequentially to all IMFs for compressing the ECG signal. The reconstruction method consists of Huffman decoding, inverse discrete cosine transform (IDCT) and spline interpolation. The proposed algorithm is compared by evaluating all 48 ECG records of MIT-BIH arrhythmia database in terms of compression ratio (CR) and the reproduction (after reconstruction) efficacy in terms of percent root mean square difference (PRD). The average values of CR and PRD are found to be 23.74:1 and 1.49, respectively. The proposed compression algorithm is also evaluated using European ST-T data base. The average CR value is found to be 23.5:1 for the selected ECG records of European ST-T data base. The compressed data obtained using European ST-T database are used for transmission over wireless medium using a GSM modem. Here it can be mentioned that the PRD for the European ST-T data base is not calculated at this point of time and will be calculated after reconstructing the original signal from the transmitted compressed data. This compression performance facilitates transmission of ECG data using a GSM modem and calculation of PRD, will be discussed in chapter 3.

CHAPTER 3

TRANSMISSION OF COMPRESSED ECG USING SMS

3.1 Introduction

ECG, an important physiological signal is used as a diagnostic tool for cardiac patient monitoring [98]. Use of computer based advanced technologies can provide faster diagnosis of cardiac patient. Signal processing applications facilitate for analysis and transfer of data from point of measurement to the physical higher level health care facility. Advances in mobile communication technology can aid to establish faster health care by means of easy transfer of medical data, along with advance infrastructure to provide advance health care [99]. In medical science, this process of transmission of medical data using telecommunication medium is termed as 'telemedicine'. Use of mobile devices has the potential to improve the flexibility in cardiac health monitoring [5]. Electronic devices like Mobile phones, general packet radio service (GPRS), global system for mobile communications (GSM) modems allows computers to communicate over wireless medium [100]. Transmission of ECG data from a patient using wireless medium, is difficult, as volume of ECG data is large. In cardiac patients the ECG data is of the order of GB. So for efficient transmission the bulky data need to be compressed sufficiently. The compressed data then can be easily transmitted using GSM modem based advanced electronic devices [101].

Mobile phones, GPRS, GSM modems use wireless technology to transmit data over a long distances in the form of short message service (SMS), multimedia messaging service (MMS), GPRS data, etc. GSM/GPRS modem (USB dongle or mobile phone) can be easily connected to computer. Transmission of data through SMS is a cost effective off-line process [23]. This work is aimed for remote health monitoring in a typical rural area. Here, the rural area is presumed to be deprived of internet connectivity. Another assumption is that the 2G mobile communication service is available in the rural area. Here, the compressed ECG signal is transmitted by SMS over wireless medium. A GSM modem is used as a signal transmitter and a GSM mobile phone is used as SMS receiver.

3.2 SMS based data transmission

Short message service (SMS) is a text messaging service provided by telecom operators [47]. These SMS can be created by mobile phones or other mobile assisted devices (e.g.: personal computers) and devices can send or receive SMS messages by communicating with the telecom network. The advantage of SMS is that text messaging is supported in all languages internationally and is supported by all mobile operators and mobile phones. Currently inexpensive SMS subscription plan is provided by almost all mobile service providers. SMS provides flexibility in sending and receiving text messages over GSM network. It is also suitable for any form of mobile phone. These advantages of extremely low cost SMS service can be utilized in mobile based health care systems. GSM technology supports various ways for SMS transmission. SMS message is popular because of some special facilities [22], which are listed as follows.

- SMS can be send and read at any time from anywhere.
- SMS can be send to switched off Mobile Phone.
- SMS is less disturbing and noisy, unlike voice call.
- SMS supports all GSM mobile phones irrespective of mobile service provide.
- SMS subscription plans are less expensive.

- SMS is a suitable technology to build wireless applications.
- SMS service is available at all places supported by mobile phone.

In wireless tele-cardiology application, the cardiac signal can be transmitted by efficient compression through computer based programming. SMS can be suitable for exchanging medical data between a patient and a physician or a doctor.

3.2.1 Computer based SMS transmission

With advancement in technology, computer plays an important role to establish communication in every field. The field of communication may be at hospitals or industry or any organization. Computer provides fast and efficient computation, there by saving time, money and resources. The available methods of communication through e-mail, mobile phone, fax, etc., can be used with computers for technological benefits. Using mobile phone or GSM modem with computer, information can be easily sent in the form of SMS, which is the popular messaging service and is economical. Two popular ways to send or receive SMS from a computer or PC [47] are described as follows.

I. SMS supported hardware connected to a computer.

II. IP SMS connection through SMS Center (SMSC).

3.2.1.1 Sending of SMS from a PC using wireless modem, mobile phone or USB dongle

Computer can send SMS through a wireless modem (or mobile phone) with a valid Subscriber Identity Module (SIM) card. A communication link is established between the wireless modem and GSM network with the aid of SIM card. The wireless modems can be connected to PC in different ways. The modems or mobile phones can be connected to PC through a USB port or a bluetooth link or data cable. Following this a standard set of AT-commands are used to instruct the wireless device or GSM/GPRS modem to send SMS messages through computer. Wireless modems also supports some extended set of AT commands (described in previous section) to control SMS message sending and receiving. The advantage is that the SMS sending process is its low cost, off line (no need of internet) service and easy to set up. The wireless connection to a computer using modem is shown in Figure 3.1.

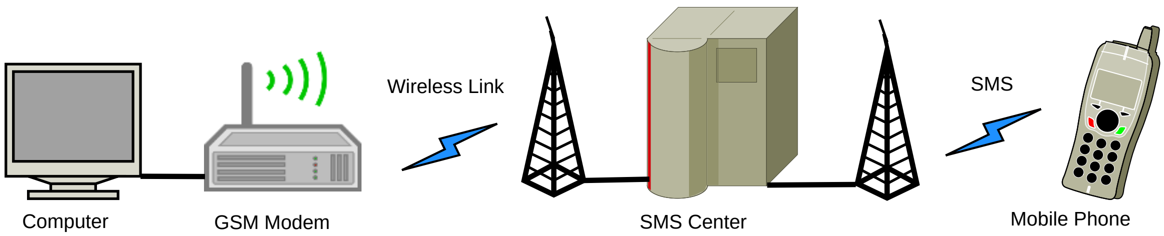

Figure 3.1: Wireless modem connection to a computer

3.2.1.2 Sending SMS from a PC using IP connection

Another way of SMS transmission is through the aid of a SMS center where the PC can be connected directly to SMSC or SMS gateway of the GSM service provider over the internet. IP SMS connections can be made using TCP/IP. This type of communication facilitates large number of SMS messages in a short time as it has a better bandwidth as compared to GSM modem. However, this service requires internet connection and may not be available in rural area.

3.2.2 Brief introduction on AT-commands

Wireless modems are controlled by the instructions known as AT-commands. Many wired dial-up modems supports some basic AT-commands that are also supported by GSM/GPRS modems and mobile phones. The basic AT-commands are ATD (Dial), ATA (Answer), ATH (Hook control) and ATO (Return to online data state). Except these basic AT-commands, GSM/GPRS modems and mobile phones support some extended AT-commands specific for GSM technology. The extended AT-command line generally begins with ‘AT’ followed by ‘+’. The prefix ‘AT’ or ‘at’ informs the wireless modem regarding the beginning of command line. Full set of GSM supports extended AT-commands is available at [47]. Some of the basic operations performed by AT commands are described as follows.

- AT-commands AT+CGMI, AT+CGMM, AT+CGSN and AT+CGMR provide the basic information like name of manufacturer, model number, IMEI (International Mobile Equipment Identity) number and software version, respectively for the mobile phone or GSM/GPRS modem.
- A subscriber's information like MSISDN (Mobile Station International Subscriber Directory Number) and IMSI (International Mobile Subscriber Identity) number can be obtained using the AT-commands AT+CNUM and AT+CIMI respectively.
- AT-commands also provide the current activity status of the mobile phone or GSM/GPRS modem.
- The sending and receiving of SMS as well as read, write or searching of phone book is posssible using AT-command.
- The security-related tasks like SIM lock, phone lock also performed by AT-commands.
- Change in the configurations of the mobile phone or GSM/GPRS modem like GSM network, SMS center address are controlled by AT-commands.

3.3 Proposed Framework

The methodology proposed here for transmission and reconstruction of ECG signal from the received SMS data are described in the following sections. For tele-cardiology application, the proposed framework is divided into two parts.

I. Wireless transmission of compressed ECG.

II. ECG signal reconstruction from the received SMS data.

3.3.1 Methodology for wireless transmission of compressed ECG

The methodology followed for GSM modem based wireless transmission of compressed ECG data consists of following steps.

- Interfacing of GSM modem with PC
- GSM modem access in PC
- Testing of GSM modem for SMS transmission

- Transmission of ECG

The work setup for the ECG signal transmission is shown in Figure 3.2.

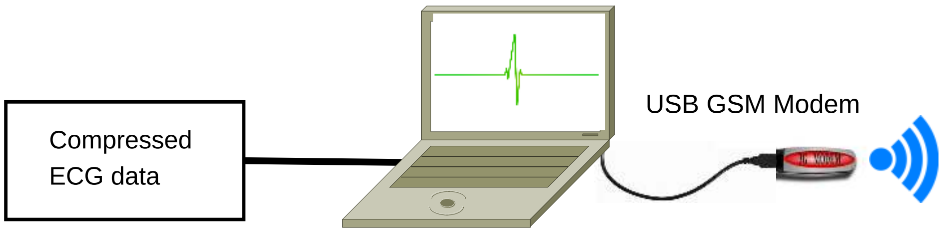

Figure 3.2: Setup for wireless ECG transmitter

3.3.1.1 Interfacing of GSM modem with PC

For experimental purpose, a 3G USB Modem ZTE data card MF 190 was used. Use of USB standard interface establishes easy plug-and-play connection of modem to any computer. Plugging the USB modem into the USB port, the modem is automatically detected and installed in PC. No external power is required to drive the modem as it draws power from the USB connection. In windows 7, data communication through serial port of the computer is made by the processes as follows (presume USB modem is plugged in).

Open the Control Panel ⇒ Click on Hardware and Sound ⇒ Click on Device Manager ⇒ Open Modems option ⇒ Click on ZTE Proprietary USB modem ⇒ Then click on the modem option to identify the COM port number at which GSM modem is connected.

3.3.1.2 GSM modem access in PC

To access a GSM modem in computer, test commands are used to check whether AT-commands are supported by the modem. The test command ‘AT’ checks the communication between GSM modem and PC. The real time work setup for transmission of compressed ECG is shown in Figure 3.3.

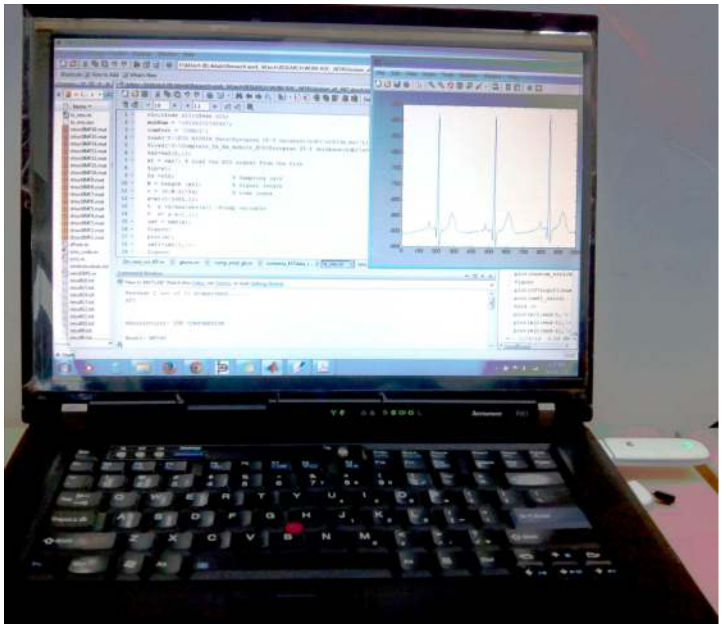

Figure 3.3: Real time work setup for wireless ECG transmission

3.3.1.3 Testing of GSM modem for SMS transmission

The command 'ATI' is used for controlling a GSM phone or modem and provides the status of the modem (i.e., Manufacturer, Model No., Revision, IMEI, other capabilities). For an example,

ATI

Manufacturer: ZTE CORPORATION

Model: MF190

Revision: BD_RELIANCEMF190V1.0.0B01

IMEI: 911133908272823

+GCAP: +CGSM,+DS,+ES

OK

The return code 'OK' indicates that 'ATI' command is executed successfully and modem is initialized.

3.3.1.4 SMS Transmission

The GSM modem uses the AT-command '+CMGS' to send a SMS message to a phone number. A mobile phone or GSM modem operates SMS in two modes, either text or PDU (Protocol Data Unit) mode. The text mode of SMS is easier to operate. First the AT-command '+CMGF' is used to set the SMS mode. The values '1' and '0' refer to SMS text mode and PDU mode respectively [102]. For an example, text mode SMS follows.

AT+CMGF=1

OK

The command line 'AT+CMGF=1' instructs the modem to operate in SMS text mode. The return result code 'OK' indicates that '+CMGF' command is executed successfully. If the operating mode is not supported by the GSM modem then 'ERROR' will be returned. Finally the command line 'AT+CMGS' instructs for sending a text message from a computer to a mobile phone number using GSM modem. An algorithm for SMS transmission process is represented in Algorithm 1.

Algorithm 1 SMS transmission using GSM modem

Load the compressed ECG data array 'x'.
$X = strconv(x)$;
`% Integer to string conversion`
$j = 0$
for $i = 0 : strlen(X)$
    if $j < 160$ **then**
        $Tx\_data(j) = X(i)$;
$j++$;
    else
        $sendSMS(Tx\_data)$;
$j = 0$;
`% reset counter`
    end if
    $i++$;
end for

A single SMS message can contain maximum of 140 bytes (1120 bits) of data, this means it can contain up to 160 characters if 7-bit (ASCII) character encoding is used. Each data point of a compressed ECG signal is separated using semicolon (;) delimiter (ASCII code is 59) before SMS transmission. Thus a concatenated SMS text message can be send by breaking a message into smaller parts where each of these parts are fitted into a single SMS message and sent to the recipient's mobile phone. For an example, the compressed ECG data obtained from first 1000 samples of European ST-T ECG record no. # e0613 are transmitted as multiple SMS. The ECG was broken into eight number of SMS messages.

3.3.2 Methodology for ECG signal reconstruction

The methodology followed for reconstruction of ECG signal from the received SMS consists of following steps.

- Transferring of multiple SMS from a mobile phone to PC.
- PC based SMS joining to reconstruct the full ECG.

The received compressed ECG data was decompressed using MATLAB software. The work setup for the ECG signal reconstruction is shown in Figure 3.4.

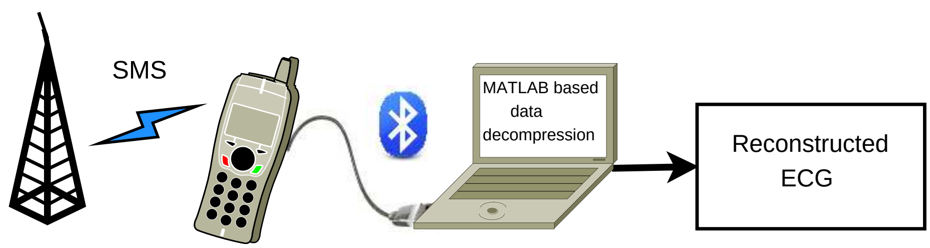

Figure 3.4: Setup for ECG signal reconstruction

3.3.2.1 Transferring of multiple SMS from a mobile phone to PC

Concatenated text messages are received in the mobile phone at the receiver. This text messages contain multiple SMS and each symbol in a SMS is delimited by semicolon. As an example, first three received SMS messages are shown in Figure 3.5. After receiving all SMS, these text messages are transferred to a PC or computer host via blue-tooth or data cable for further processing.

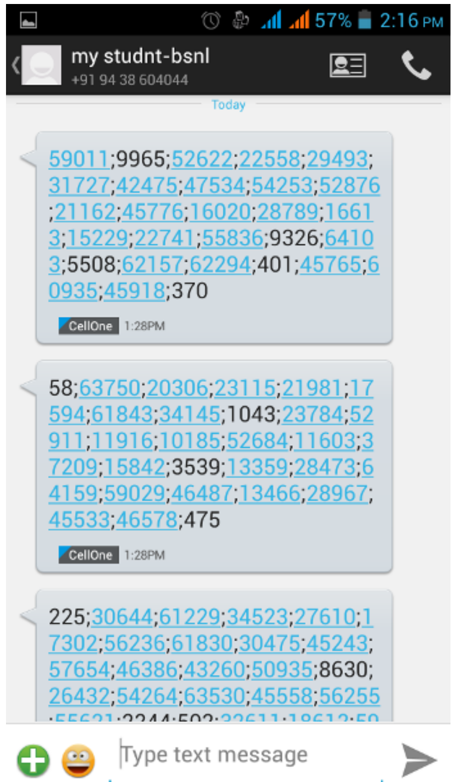

Figure 3.5: Received SMS messages

3.3.2.2 Reconstruction using SMS joining

The received multiple SMS messages are joint to form single text message. These text messages are then converted to unsigned integer of 16 data type representation. Following this the unsigned data are further processed to reconstruct the original signal using the decompression technique as discussed in Chapter 2. Text data after converted to unsigned integer 16 data type, are fed as input to the decompression block. The decompression is carried out through Huffman decoding. Inside the Huffman decoding block, a Huffman to normal data compression algorithm decompresses the data. The decompressed data is then interpolated through cubic- spline interpolation to get back the original ECG signal. The work flow diagram of PC based ECG signal decompression from the received SMS message is shown in Figure 3.6.

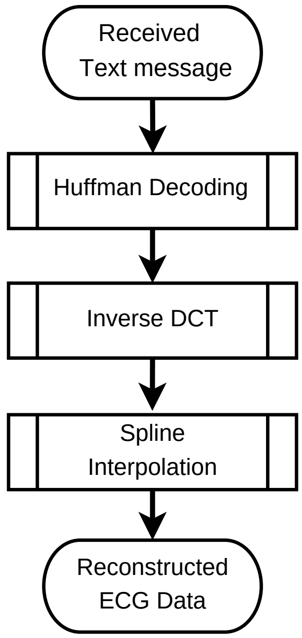

Figure 3.6: Flow chart for reconstruction of ECG signal

3.4 Experimental Results and Discussions

As mentioned in previous chapter, ECG records from European ST-T database [6] are used for data compression. The compressed ECG data are then transmitted over wireless medium for remote patient monitoring. For an example, in this experiment, first 1000 samples of ECG record no. # e0613 from European ST-T database are transmitted by splitting the message into SMS. The SMS messages are sent as concatenated SMS messages. The concatenated SMS dispatch process is presented as screenshot in Figure 3.7. The effectiveness of the decompression technique to reconstruct the original signal is evaluated using the ECG records of European ST-T database. The performance parameter, percent RMS difference (PRD) is evaluated using the (2.4). The experimental values of PRD for European ST-T database are given in Table 3.1. In Figure 3.8 the original ECG signal and the reconstructed signal were plotted. A magnified version of a part of the plot (represented by straight line) is shown in the small window. From the Figure 3.8, it is evident that the ECG signal was reconstructed with less error. The difference between the original ECG signal and reconstructed ECG signal, error, was

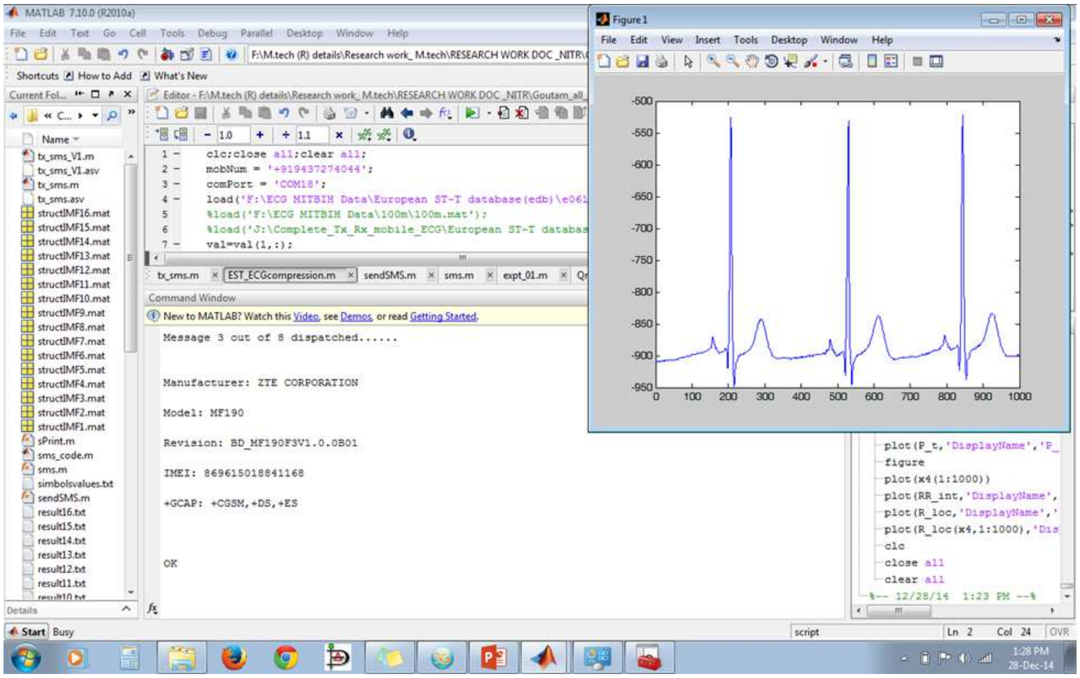

Figure 3.7: The SMS based ECG transmitter output

Table 3.1: Evaluation of PRD for European ST-T database

ECG Record	PRD
e0105	0.71
e0112	6.92
e0122	0.384
e0127	0.56
e0207	4.22
e0211	2.31
e0404	0.1
e0417	0.243
e0606	0.13
e0613	0.22
e0615	0.46
e0704	0.24

evaluated. The error square (ε^2) signal was calculated as

$$\varepsilon^2 = [\ (Original\ ECG)\ -\ (Reconstructed\ ECG)\ ]^2$$

Figure 3.9 represents the normalised error square (in dB). It is seen from the Figure 3.9, that the error square is marginal.

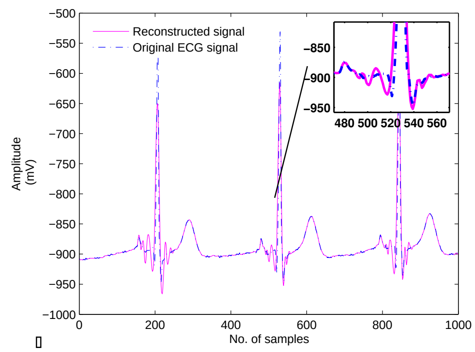

Figure 3.8: Original and reconstructed ECG signal

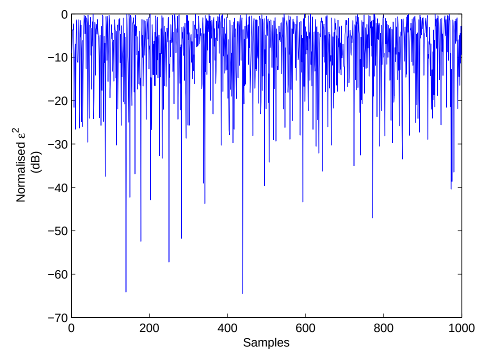

Figure 3.9: Normalised error square signal in dB

3.5 Summary

This chapter presents, a technique for transmission of compressed ECG data using wireless medium and also reconstructs the ECG signal from received data. For transmission purpose, a USB GSM modem is used with computer to send the compressed ECG signal as SMS message. Modem is controlled by AT-command in a PC. The compressed data used is the output obtained from the previous chapter based on Empirical Mode Decomposition (EMD). All the SMS messages are received successfully in a mobile phone used for this purpose at receiver section. The received SMS messages are transferred to PC using blue-tooth and the data decompression algorithm is carried out using MATLAB software to reconstruct the ECG signal. The reconstructed ECG signal is then compared with the original ECG signal and an error signal is found. A reconstruction parameter PRD is used to evaluate this technique. The average PRD is found to be 1.38 for selected records of European ST-T database. The low value of PRD means the reconstructed signal contains less error. Hereafter the reconstructed ECG signal will be further processed for detection of cardiac disorders. Detection of cardiac disorders from the received signal is presented in Chapter 4.

CHAPTER 4

DETECTION OF CARDIAC DISORDERS LIKE BRADYCARDIA, TACHYCARDIA AND ISCHEMIA

4.1 Introduction

Determination of different wave peaks in the ECG signal are important for detection of cardiac disorders. A full cycle of ECG signal is generated in every heartbeat. The normal rhythmic contraction and expansion of the arteries inside the human body is known as heartbeat. One of the important parameters to evaluate a person' s health is the heart rhythm. Heart rhythm defines the speed of the heartbeat and is useful for heart rate (HR) calculation. The heart rate is the number of heartbeats per unit of time. Generally HR is measured in beats per minute (bpm). A normal person is identified by the heart rhythm and HR calculation. The abnormal heart rhythm causes slow or fast heartbeat [15]. Early detection of such abnormal heart rhythm is most important to avoid serious cardiac disorders. The HR value is calculated and compared with normal HR range to identify various heart rhythm abnormalities like bradycardia and tachycardia. The heart rate below and above normal range are called bradycardia and tachycardia respectively. Another common heart disorder which causes heart attack is known as ischemia or cardiac ischemia. Ischemia or heart stroke is a cardiovascular disorder which affects the heart and the blood vessels. Here, the coronary arteries become narrowed by atherosclerosis which restricts the flow of blood and oxygen to the heart. This can lead to brain cells to die which can creates a cardiac disorder known as ischemia [103]. Detection of ischemia takes long time to analyze.

Many techniques have been developed for detection of cardiac disorders in [16, 50, 61, 63, 104, 105]. The cardiac dysrhythmia techniques [50, 52, 53, 104] fails to provide more analysis on the information content in the ECG signal for complete diagnosis. The technique reported [52, 55, 56] uses PCA, NN classifier, etc., which adds complexity to the system. The ischemia detection techniques [16, 55, 61, 106] takes more computation time to estimate the ST-segment and or T-wave end points for diagnosis of ischemic disorder. The detection process takes more time if analyzed by doctor using long duration ECG data. So an automatic technique is required for quick detection of cardiac disorders. The location of ECG wave peaks are required for detail analysis and automatic diagnosis of cardiac dysrhythmia. The ECG beat classification is essential for automatic detection and diagnosis of ischemic episodes in a long duration electrocardiogram. The key to ischemic episodes detection is the ST-segment deviation and T-wave amplitude changes [107]. Most importantly the parameter, ST-segment deviation is expressed as polarity change relative to isoelectric line. The isoelectric line is the baseline, typically measured between the T-wave offset and the preceding P-wave onset of electrocardiogram. Isoelectric line is used as a reference for measurement of ST-segment deviation and T-wave amplitude changes [108].

In the preceding chapter, the process of transmission of compressed ECG signal was demonstrated. The reconstruction of compressed ECG signal from its compressed samples was successfully demonstrated. The reconstruction process is done by the doctor and hence it is possible to analyze the ECG data for detection of cardiac abnormalities. This chapter describes the process of cardiac abnormality detection.

4.2 Proposed framework

The proposed work consists of five stages [109]. The block diagram of overall process is shown in Figure 4.1. In first stage, ECG recording is pre-processed to reduce noise components and QRS-complexes are detected by filtering. In the next stage, consecutive QRS-complexes are used to detect heart rhythm abnormality. Thereafter, ECG feature extraction is carried out to locate other ECG wave peaks, ST-segment and T-wave. In the next stage, beat classification is done as normal or ischemic using certain rule, based on medical knowledge and the final stage provides the identification of ischemic episode which is based on the detection of two or more consecutive ischemic windows using first 30s of each ECG recording.

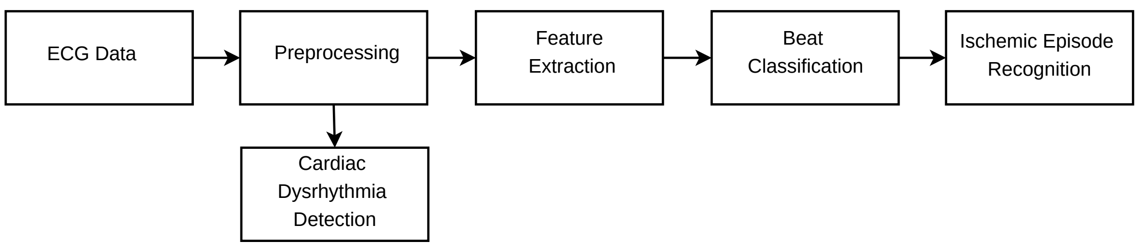

Figure 4.1: Block diagram for cardiac disorder detection

The complete flow diagram of proposed cardiac disease detection process is given in Figure 4.2.

4.2.1 Preprocessing

Pre-processing of raw ECG signal is required for removal of noises consisting of muscle noise, baseline wander and T-wave interference, etc., [110]. The P- and T-wave frequency generally lies between 0.5Hz and 10Hz. Sometimes these frequency coincides with the baseline noise having a low frequency range of 0-0.8Hz [1]. Hence, it is important to remove the baseline noise for true peak detection in ECG signal. ECG signal is first amplitude normalized and then band pass filter (5-15Hz) is used to reduce the effect of noises. The band pass filter is composed of cascaded high-pass and low-pass integer filters [111]. The functionality of pre-processing stage is elaborated in following sections.

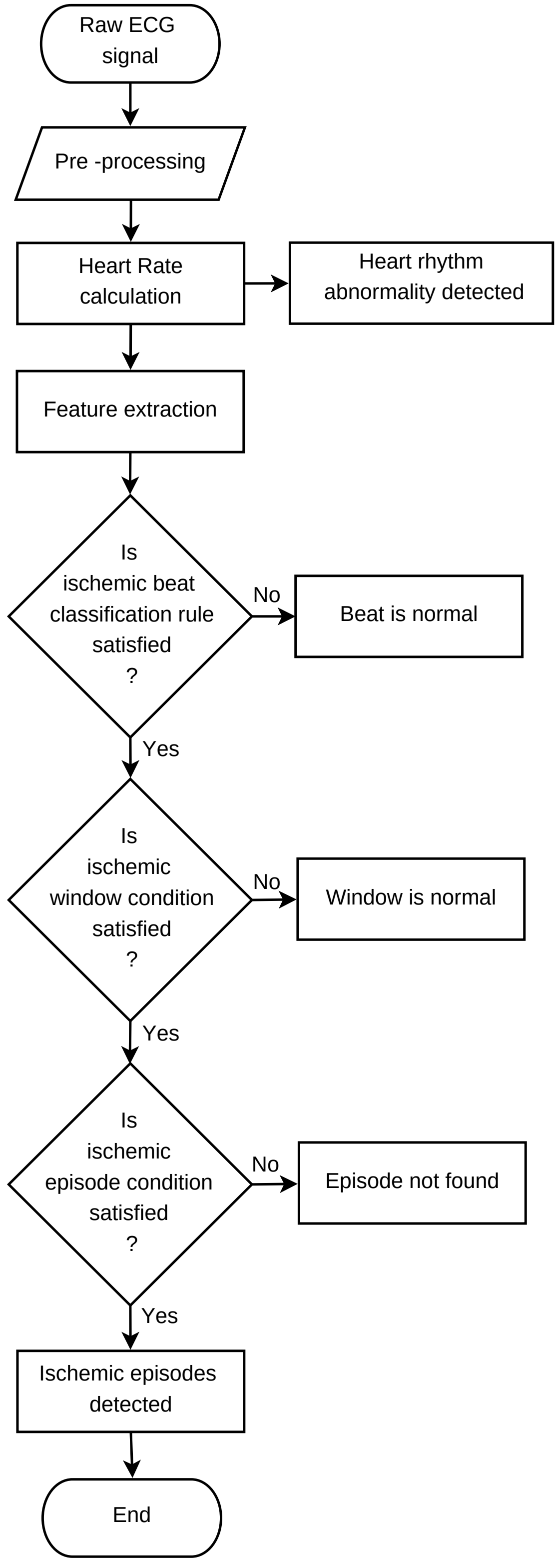

Figure 4.2: Complete flow diagram of proposed framework

4.2.1.1 QRS-complex detection

In general the term heart beat refers to the entire ECG cycle of PQRST, but the QRS-complex represents the instant that a beat occurs. The QRS-complex portion of the ECG is the most distinctive feature for easy cardiac disorder identification. The duration of the QRS-complex is normally less than or equal to 100ms [9]. R-peak is the most prominent and the tallest peak in determination of QRS-complex. The detail processes for filtering and QRS-complex approximation is based on algorithm by J. Pan and J. Tompkins [111]. The block diagram of QRS-complex detection process used by Pan and Tompkins algorithm [111] is presented in Figure 4.3.

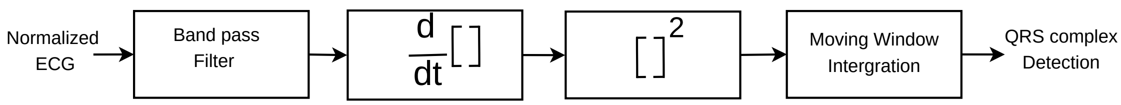

Figure 4.3: Stages of QRS-complex detection

Step 1: Amplitude normalized ECG signal is filtered using a band pass integer filter. The desirable pass-band to maximize the QRS energy is approximately 5-15Hz [111].

Step 2: The band pass filtered signal is differentiated for finding high slopes which normally distinguishes QRS-complex from other ECG waves.

Step 3: The differentiated signal is squared point by point to make all the data points positive and does the nonlinear amplification to emphasize the higher frequency (i.e. ECG frequencies) in the differentiated signal.

Step 4: The squared waveform then passes through a moving window integrator to obtain waveform feature information in addition to the slope of the R-wave. The width of window is chosen to be long enough to include the widest QRS-complex.

Step 5: The thresholds are calculated using running estimate of signal peak and noise peak. The thresholds are automatically adjusted to overcome the noise peak and QRS-complex is detected.

The input ECG signal and signals after normalization are shown in Figure 4.4. The filtered ECG signal after differentiation and location of RR-interval is shown in Figure

4.5.

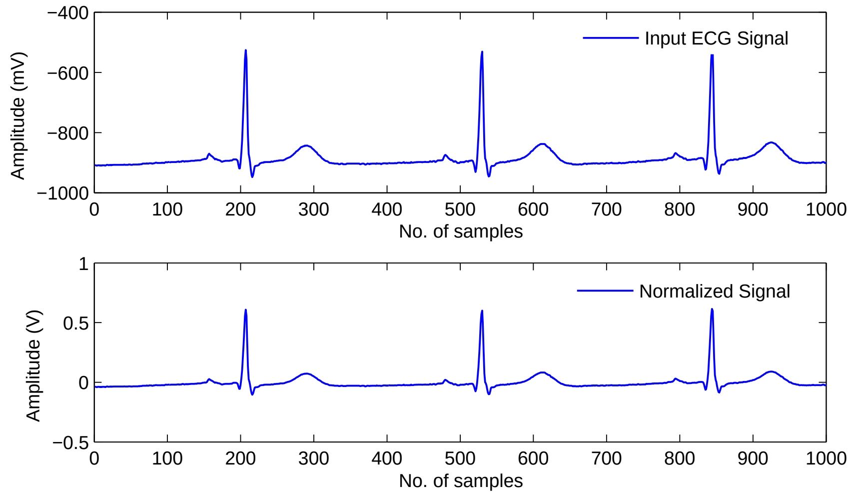

Figure 4.4: Different signals during filtering

(a) ECG signal (European ST-T record tape no. # e0613) (b) Normalized signal

4.2.1.2 RR-interval determination

R-peak is the tallest peak in QRS-complex. RR-interval is determined by finding the time difference between two consecutive R-peaks [112].

4.2.1.3 Heart Rate calculation

The heart rate (HR) is calculated from the extracted features of ECG signal by finding the inverse of RR-interval. HR is expressed in beats per minute (bpm) and the normal range of HR is 60-100 bpm. The formula used to calculate heart rate is $\frac{60}{t_{rr}}$ bpm [1], where $t_{rr} = \frac{RR\text{−}interval(in\ \ samples)}{sampling\ \ frequency}$. Here the sampling frequency of 250Hz is used as per European ST-T database [6]. Hence HR value is calculated as $\frac{250}{RR\text{−}interval\ \ (in\ \ samples)} * 60$ beats/min. The HR value is used to identify slow or fast heart rhythm.

4.2.2 Heart rhythm abnormality detection

The calculated heart rate value is compared with normal range to detect the heart rhythm abnormalities like bradycardia and tachycardia. The fast or slow heart rhythm

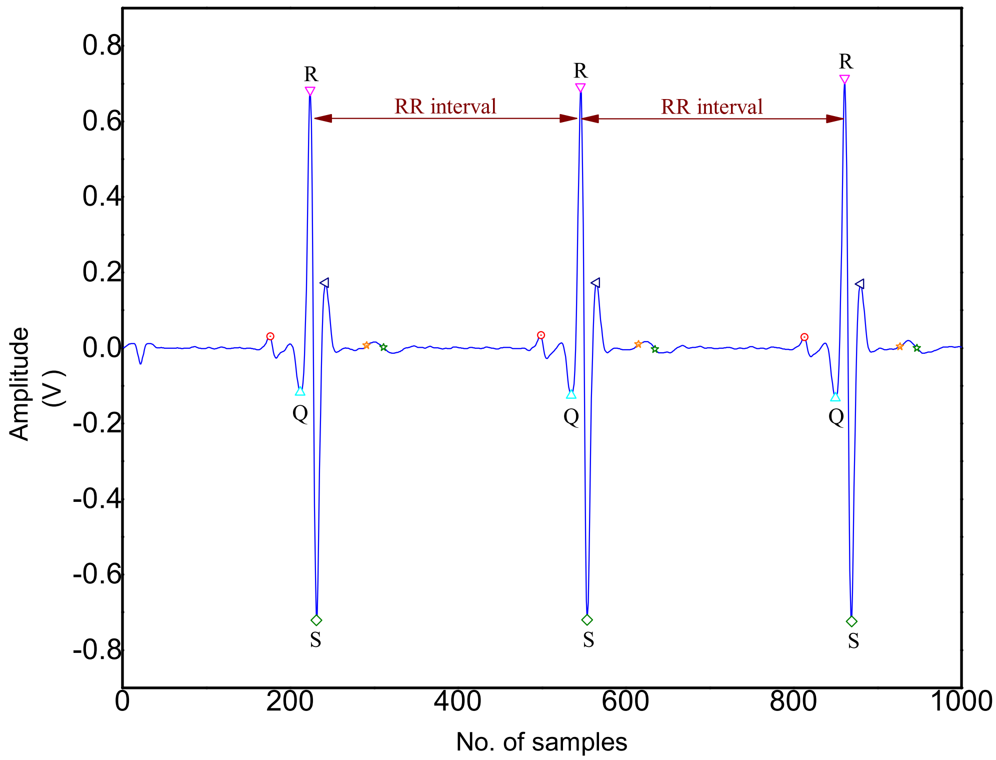

Figure 4.5: RR-interval determination using QRS-complex peaks

is identified by calculating HR value. The HR value is less than 60 bpm then it is termed as slow heart rhythm or bradycardia and if HR is greater than 100 bpm then it is called as fast heart rhythm or tachycardia [15].

4.2.3 Feature extraction

The ECG features for ischemia detection is determination of ST-segment and T-wave alternation from QRS-complex. Pan and Tompkins algorithm [111] is one of the most popular algorithm to find QRS-complex. Other features like P-wave location, J-point location, T-wave, T_{ON} and T_{OFF} locations, isoelectric line and ST-segment location are extracted by using the previously located Q-, R- and S-wave peaks.

4.2.3.1 P-wave Location

A threshold level is used with reference to the normal range of ECG segments to locate P-wave. The normal PR-interval ranges from 120-200ms whereas amplitude and duration of P-wave are 0.25mV and 80ms respectively [1].

4.2.3.2 J-point Location

The J-point is the junction between the QRS-complex and the ST-segment of ECG signals [108]. It is also the first point where the waveform flattens out to the right after QRS-complex. The J-point location is normally at the end of QRS-complex which has normal range of 80-120ms.

4.2.3.3 T-wave, T_{ON} and T_{OFF} Location

After determining the location of R-peak and J-point, the peak of T-wave is estimated as maximum elevation between R-peak + 400ms and J-point + 80ms. T_{ON} and T_{OFF} is then estimated by considering 35ms duration from left and right of the T-wave peak respectively [1].

4.2.3.4 Isoelectric Line and ST-segment Location

Isoelectric line is the baseline or almost zero amplitude level. The base line is chosen as the flat line between P-wave and Q-wave. The location for isoelectric line was estimated by finding the start and end point of all zero slope amplitude ECG level. All the extracted ECG features are as shown in Figure 4.6. ST-segment is located 80ms after J-point when cardiac rhythm is less than 120 bpm and 60ms after J-point when the cardiac rhythm is more than 120 bpm [113].

4.2.4 Ischemic beat classification

The ST-segment and T-wave are the two features generally used by cardiologist for ischemic beat classification. The beat classification is based on clinical rules as reported in [105]. The rules considers as, the beat is ischemic when ST-deviation is more than 0.08mV above or below the isoelectric line [114] and the beat is ischemic when T-wave is inverted or flattened [105]. The T-wave inversion is measured considering T-wave amplitude variation (positive or negative) with respect to the isoelectric line for first 30s

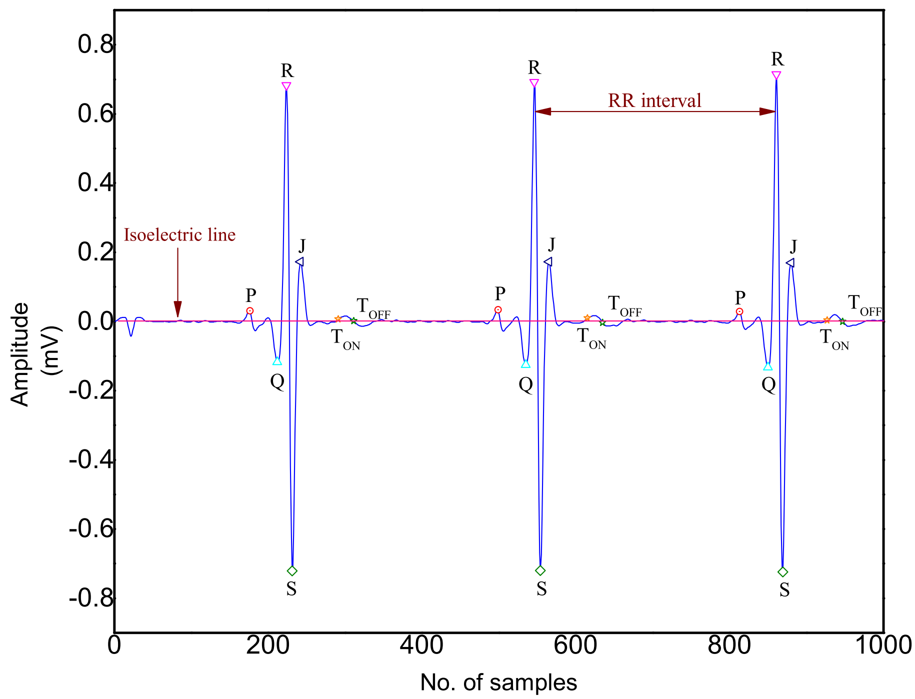

Figure 4.6: ECG signal extracted wave peaks and points with baseline

duration ECG. The ischemic beat classification process is represented in Algorithm 2 as per the reported technique in [105].

Algorithm 2 Ischemic beat classification

if (ST- segment $\leq$ 0.08mV) (or) (ST- segment $\geq$ 0.08mV) (or) (T inverted or T$\rightarrow$ 0mV) **then**
  The beat is ischemic
else The beat is normal
end if

4.2.5 Ischemic episode recognition

As per the recommendation of ESC (European Society of cardiology) the ischemic episode detection procedure considers minimum 30s duration of signal. The ischemic episode detection process considers a sliding window technique which searches the sequences of ischemic beats exist for 30s or more. The first sliding window includes first 30s of the signal and the technique proceeds moving the window one beat at a time keeping window duration of 30s. Normally a threshold value of 75% criteria detects ischemic windows [105]. The ischemic window is detected if the 30s window contains more or equal to 75% of ischemic beats [105]. Ischemic episode recognition is the process to identify consecutive 30s windows and 75% of the 30s window must have ischemic beats [115]. The ischemic episode left boundary corresponds to the beginning of the first window in the series and the right boundary corresponds to the end of the last window [105]. The ischemic episode detection process is represented in Algorithm 3 as per the reported technique in [105].

Algorithm 3 Ischemic episode detection

```
if ([(No. of Ischemic beats) /(All beats)] ≥ 0.75) then
    The window is ischemic
else The window is normal
end if
if (No. of consecutive ischemic window ≥ 2) then
    Ischemic episode is identified
end if
```

4.3 Experimental Results and Discussions

The effectiveness of this technique is evaluated using ECG records from European ST-T database [6]. The heart rhythm abnormalities i.e., bradycardia and tachycardia are detected by comparing the calculated HR value with the normal range of heart rate. The results for cardiac dysrhythmia detection using European ST-T database is presented in Table 4.1. Ischemic episode detection performance is evaluated in terms of the parameters sensitivity (Se) and positive predictive accuracy (PPA). The sensitivity measures the ability to detect ischemic episode where as PPA gives estimation likelihood that a detected episode is a true ischemic episode [116]. These parameters are evaluated as:

$$Se = \frac{TP}{TP + FN} \times 100$$

$$PPA = \frac{TP}{TP + FP} \times 100$$

where, TP = True Positives (Correctly detected event), FP = False Positives (Erroneously detected non event), FN = False Negatives (Erroneously missed event) As mentioned above, TP represents the annotated beats/episodes in the database, FN corresponds to the annotated beats/episodes that were not detected and, finally, FP denotes

Table 4.1: Heart rhythm abnormalities identification

ECG Data	RR- interval (ms)	HR (bpm)	Heart rhythm abnormality
e0105	826	73	Normal heart rhythm
e0112	748	80	Normal heart rhythm
e0122	593.3	101	Tachycardia
e0127	731	82	Normal heart rhythm
e0207	756	79	Normal heart rhythm
e0211	436.5	137	Tachycardia
e0404	794	76	Normal heart rhythm
e0417	616.8	97	Normal heart rhythm
e0606	661	91	Normal heart rhythm
e0613	849.3	71	Normal heart rhythm
e0615	718	84	Normal heart rhythm
e0704	688	87	Normal heart rhythm

the number of beats/episodes that were not annotated in the database, but that were incorrectly identified by the algorithms [103]. The correctly detected or true positive events are the reference annotations available in European ST-T data base. The ischemic episode detection results are presented in Table 4.2.

Table 4.2: Results of ischemic episode detection

ECG Data	Number of 30s windows	Number of Ischemic windows	Original No. of Ischemic ST episodes	Number of Ischemic ST Episodes detected	*TP*	FP	FN	% Se	% PPA
e0105	3693	694	11	8	8	0	3	72.73	100
e0112	3672	36	5	6	5	1	0	100	83.33
e0122	6245	2077	2	3	2	1	0	100	66.67
e0127	5053	316	7	6	6	0	1	85.71	100
e0207	3815	14	6	3	3	0	3	50	100
e0404	3884	30	5	3	3	0	2	60	100
e0417	5188	31	3	3	3	0	0	100	100
e0606	4415	4381	2	3	2	1	0	100	66.67
e0613	4097	465	11	5	5	0	6	45.45	100
e0615	3832	3811	3	3	3	0	0	100	100
e0704	5376	5368	3	3	3	0	0	100	100

From the result it is seen that, this methodology detects 3693 number of 30s windows, 694 number of ischemic windows and 08 numbers of ST episodes for the ECG recording e0105. The number of available ischemic ST episodes is 11 as per the European ST-T database. This technique achieves an average sensitivity and positive predictive accuracy of 83.08% and 92.42% respectively. The performance of the other reported algorithms are also discussed like, Silipo *et al.* [114] presents an algorithm for ischemic episode detection which could determine average sensitivity of 76% and average positive predictive accuracy of 85% using a recursive neural network. Vila *et al.* [117] uses fuzzy approach for the detection of ischemic episodes, when the average sensitivity and average positive predictive accuracy parameters were of 84% and 90%, respectively. The algorithm presented by Maglaveras *et al.* [55] detects average ischemic episode detection sensitivity is 88.62% while positive predictive accuracy is 78.38% using an adaptive back propagation neural network. Use of Hidden Markov Model for ischemic episodes detection was introduced by Andreao *et al.* [118] that achieved an average sensitivity of 83% and a average positive predictive accuracy of 85%. Most of the earlier reported techniques [55,114,117] are based on classifiers which makes computation more complex. For timely detection, an automatic technique is used for ischemic episode detection and it provides good accuracy in terms of average sensitivity and positive predictive accuracy.

4.4 Summary

The proposed technique first evaluates the heart rate. The predefined normal HR range is used to identify slow or fast heart rhythm. The abnormal heart rhythm i.e., bradycardia and tachycardia are detected by this process. The ischemia detection technique finds the consecutive 30s ischemic windows to identify ischemic episodes. The performance measurement parameters are calculated using European ST-T database. The performance of this technique improves in terms of average sensitivity and average positive predictive accuracy and it is practically useful for diagnosis of other diseases. The inclusion of heart dysrhythmia identification to ischemic episode detection technique provides an improved diagnostic tool for an automated cardiovascular disease detection system.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE OF WORK

This thesis presents a novel technique for ECG signal compression so that it can be sent over wireless network using a set of SMS. The compression is based on empirical mode decomposition (EMD). The high adaptability of EMD makes it popular in non-stationary signal processing. Efficient and economical transmission of compressed signal using wireless technology has been demonstrated. Here, ECG signal after compression is transmitted as a series of SMS. A mobile phone can be used to receive the transmitted text data and subsequently the decompression process is carried out to reconstruct the ECG data. The physician or the doctor at a hospital can analyse the reconstructed signal for detection of cardiac disorders like heart rhythm abnormalities and ischemic episodes. The real time implement of this mobile health care system may be useful for reliable and economical diagnosis of cardiac patients located at remote areas. The experimental studies reported in this thesis are briefly summarized in the following sections. All the algorithms presented in the thesis have been implemented using MATLAB Version 7.10, Release name R2010a, Number 23 of Mathworks Inc. All experiments are carried out on a single computer having Intel Core i5 computer, processor 3.20Ghz with 4GB RAM and Windows 7 operating system.

5.1 Conclusions

- Empirical mode decomposition (EMD) technique was used in this thesis to compress the ECG signal. EMD technique first decomposes the ECG signal into several intrinsic mode functions (IMFs). The last IMF is called the residue. First two noisy IMFs (i.e., IMF 1 and IMF 2) are removed and the rest IMFs and residue are used to compress the signal. Then downsampling is applied to these IMFs and residue. The downsampled signals are summed up and fed as input to the next stage. Discrete cosine transform (DCT), window filtering and Huffman encoding techniques are then used sequentially to compress the ECG signal. The reconstruction method consists of Huffman decoding, inverse discrete cosine transform (IDCT) and spline interpolation. The reproduction (after reconstruction) efficacy is measured in terms of percent root mean square difference (PRD). Experimental results show that the proposed technique provides high CR compared to other techniques. PRD value is also comparable to lossless compression techniques.

- A low cost off-line text messaging service, SMS is used for transmission of compressed ECG. For experimental purpose a PC / laptop with GSM modems was used to send the ECG signal over wireless link. The SMS messages were sent to a mobile phone and the received SMS messages were processed for decompression to reconstruct the ECG signal. Experimental result shows comparable PRD which can provide better diagnostic information in the reconstructed data.

- A detection algorithm has been proposed to detect heart rhythm abnormalities and ischemic episodes. The proposed technique first, evaluates the heart rate (HR) and then uses the predefined normal HR range to identify slow or fast heart rhythm i.e., bradycardia or tachycardia respectively. In ischemia detection algorithm first, preprocessing of the signal was performed which involves normalization and filtering. Next feature extraction, beat classification and ischemic episode recognition are used sequentially to identify ischemic episodes. A health care system is implemented here. ECG signal is first, compressed and transmitted over wireless medium. Next, at the receiver the signal is decompressed to reconstruct the original signal. Then the detection technique is carried out to identify various cardiac disorders. Experimental results show that the proposed technique provides high sensitivity (Se) and high positive predictive accuracy (PPA) compared to other techniques. Implementation of this, system can facilitate mobile health care.

5.2 Future Works

In this research work, a remote cardiac patient monitoring method is described to diagnose the cardiac disorders. In future, more works can be implemented for faster and advanced health care. Some of the future works are described below.

- This work has been done for a single patient communicating with doctor over wireless network. However, if multiple patient communicate with doctor then the doctor can not recognize each SMS individually. In future, this work can be extended to a number of patients communicating with doctor simultaneously with use of different data frames.

- The work intended in this thesis was is to provide remote health care in a typical rural area. Here, it is presumed that 2G mobile communication service is available and there is no internet connectivity. In future, an automatic internet based transmission system can be designed to harness the high speed internet service where available.

- Currently Windows and Android operating system based smart phones are widely used. These operating systems facilitate development of applications for different requirement. In future, tele-cardiology applications for ECG transmission and detection can be developed. These applications will have potential to provide coronary health care to remote areas.

- The proposed detection technique can be extended to detect other cardiovascular disorders like bundle branch block, wolff- parkinson- white syndrome, premature ventricular contraction, myocardial infraction, etc., with little modification in detection algorithms. Advanced pattern recognition techniques can be applied for detection of ischemia and other types of cardiac disorders.

- Implementation of a stand-alone low cost hardware system using an embedded system platform can help to make quality health care affordable to cardiac patients in remote areas. Once implementation is completed, survey on doctor's opinion can be made for the fidelity of the system.

- ECG image compression and reconstruction algorithms can be developed for remote patient monitoring system. Also real time noises can be introduced with ECG signal to see the robustness of the algorithms. Different filtering techniques can be used in ECG signal compression and reconstruction algorithms to make the performance better.

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