Chapter 1: Introduction

1.1 Automatic Analysis of Biological Signals

Human body is an extremely complicated system comprising of a number of physiological processes. There are a number of biological signals like electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG), phonocardiogram (PCG), vibroarthogram (VAG) etc. that are generated from these physiological phenomena being the source of information of the corresponding process. Thus it is a requirement to capture and measure these signals for clinical analysis of different pathological conditions of the subject. Biomedical signal analysis and diagnostics find the application of electronics after the establishment of clinical electrocardiograph by Dutch physician William Einthoven in the year 1903. Since then, electronic equipments became a counterpart of medical diagnosis. With the development of digital computers, some biomedical data handling jobs are assigned to it, which reduces the human effort and increases the speed of operation. Gradually logical operations are also left to some extent for the computers according to the in-built programs which leads to automation. In this thesis the method of computerized automatic analysis of ECG signals is described for monitoring and diagnosis of Cardiac abnormalities.

1.2 Introduction to Electrocardiogram

The electrocardiogram (ECG) is a, graphic depiction of the electrical forces generated by the heart in association with cardiac contraction and relaxation. These electrical forces spread from the heart to the
surface of the body from where they can be picked up by appropriately placed electrodes and recorded in the form of a graph called electrocardiogram (ECG). A typical ECG is shown in figure 1.1.

![Figure 1.1: A typical Electrocardiogram waveform](image)

It would be worthwhile to review the basic principles of cardiac electrophysiology before venturing into the intricacies of the vast and intriguing subject of electrocardiography. Not only would this permit a smooth journey through the subject but it will also facilitate the understanding of normal and abnormal ECG patterns in the right perspective.

1.2.1 The Heart

Duo to a pumping operation by sequential contraction and relaxation, heart provides oxygen and nutrients to the organs and tissues of the body through blood circulation. In the human body the heart is situated slightly to the left of the middle of the thorax, behind the sternum. It is enclosed by a membrane known as myocardium. It weighs about 300-350 gm in an adult. Heart is made up of four chambers - the two atria (left and right) being the thin walled receiving chambers and the two ventricles (left and right) being the thick-walled pumping chambers as shown in figure 1.2.

Electrical activation of heart is initiated by an impulse which is originated from a group of cells that comprise the pacemaker of the heart. The cardiac pacemaker possesses the property that it can generate
the electrical impulses automatically. The usual pacemaker under normal conditions is the sinoatrial node or SA node situated in the upper part of the right atrium, close to the entry of the superior vena cava. The SA node normally discharges at a rate of 60 to 100 impulses per minute, which is the normal heart rate. The SA node is under the influence of the autonomic nervous system and its hormones which can vary the heart rate. Bachmann's bundle carries the impulse to the left atrium from SA node.

This automatically generated electrical impulse spreads over the heart through a specialized conduction system. When the SA node sends out the impulse, the first place it goes is to the atrioventricular (AV) node. While the SA node sets the rhythm of the pulse, the AV node sets the rhythm of the heart contractions. It delays the signal on its way to the ventricle about a tenth of a second, giving the atrium time to contract first. If the atrium and the ventricle contracted at the same time, the ventricles would push out their blood before they were totally full, resulting in low blood pressure, among other problems.
After the brief delay in the AV node, the impulse travels downwards towards the ventricles through a specialized conducting system called the Bundle of His. It consists of multiple longitudinal tracts which divide into separate branches. It primarily divides into two branches, a right bundle branch (RBB) which traverses the right ventricle and a left bundle branch (LBB) that traverses the left ventricle (Figure 1.3). A small septal fascicle originates from the proximal portion of the left bundle branch to activate the interventricular septum from the left in a rightward direction. Incidentally, this is the first portion of the ventricular region to be electrically activated from the His bundle. The left bundle branch further divides into a left posterior fascicle and a left anterior fascicle. The left posterior fascicle is a broad band of fibres spreading over the posterior and inferior surfaces of the left ventricle while the left anterior fascicle is a narrow band of fibers spreading over the anterior and superior surfaces of the left ventricle.

Having traversed the bundle branches, the electrical impulse passes into their terminal ramifications or Purkinje fibers. These Purkinje fibers traverse the thickness of the myocardium from the endocardial surface (surface facing cavity) to the epicardial surface (outer surface). In fact, it is the propagation of impulses through these fibres that effects the electrical activation of the myocardium.
1.2.2 Lead System

During activation of the myocardium, electrical forces or action potentials are propagated in various directions. These electrical forces can be picked up from the surface of the body by means of electrodes and recorded in the form of an electrocardiogram. A pair of electrodes, that consists of a positive and a negative electrode and is oriented to record these electrical forces as viewed from one side of the heart, constitutes an electrocardiographic lead. The position of these electrodes can be varied in such a way that different leads are obtained, which are oriented in different relationships with the heart.

There are twelve conventional ECG lead placements that constitute the routine 12-lead ECG. The 12 ECG leads are:

- Limb leads or extremity leads-six
- Chest leads or precordial leads -six

The limb leads are derived from electrodes placed on the limbs. An electrode is placed on each of the three limbs namely right arm, left arm and left leg. The right leg electrode acts as a grounding electrode.

The limb leads are further categorized as:

a. Standard limb leads-three
b. Augmented limb leads-three

❖ Standard Limb Leads

![Orientation of bipolar limb leads](Figure 1.4: Orientation of bipolar limb leads)
Introduction

The standard limb leads obtain a graph of the electrical forces as recorded between two limbs at a time. Therefore, the standard limb leads are also called bipolar leads. In these leads, one limb carries a positive electrode and the other limb carries a negative electrode. There are three standard limb leads namely:

(i) Lead I
(ii) Lead II
(iii) Lead III

I. Lead I - In this lead, left arm electrode is positive and right arm electrode is negative.

\[ \text{i.e., Lead I} = V_{LA} - V_{RA} \]  \hspace{0.5cm} (1.1)

II. Lead II - In this lead, left leg electrode is positive and right arm electrode is negative.

\[ \text{i.e., Lead II} = V_{LL} - V_{RA} \]  \hspace{0.5cm} (1.2)

III. Lead III - In this lead, left leg electrode is positive and left arm electrode is negative.

\[ \text{i.e., Lead III} = V_{LL} - V_{LA} \]  \hspace{0.5cm} (1.3)

These are standard bipolar limb leads. Figure 1.4 shows the orientation of these leads.

❖ Augmented Limb Leads

![Orientation of limb leads](image_url)

Figure 1.5: Orientation of unipolar limb leads
The augmented limb leads obtain a graph of the electrical forces as recorded from one limb at a time. Therefore, the augmented limb leads are also called unipolar leads (figure 1.5). In these leads, one limb carries a positive electrode, while a central terminal called Wilson Central Terminal (WCT) represents the negative pole which is actually at zero potential. There are three augmented limb leads as:

(i) Lead \( aV_R = V_{RA} - V_{WCT} \) (1.4)
(ii) Lead \( aV_L = V_{LA} - V_{WCT} \) (1.5)
(iii) Lead \( aV_F = V_{LL} - V_{WCT} \) (1.6)

Where, \( V_{WCT} = \frac{1}{3} (V_{LA} + V_{RA} + V_{LL}) \) (1.7)

- Lead aVR - In this lead, the positive pole is the right arm electrode.
- Lead aVL - In this lead, the positive pole is the left arm electrode.
- Lead aVF - In this lead, the positive pole is the left leg electrode.

The Chest Leads

![Figure 1.6: Orientation of chest leads](image)
The chest leads are derived from electrodes placed on the precordium in designated areas. An electrode can be placed on six different positions on the chest, each position representing one lead. Lead positions are shown in figure 1.6. Accordingly, there are six chest leads namely:

- **Lead V₁**: It is located over the fourth intercostal space, just to the right of sternal border.
- **Lead V₂**: It is located over the fourth intercostal space, just to the left of sternal border.
- **Lead V₃**: It is located over a point midway between V₂ and V₄ (see V₄ below).
- **Lead V₄**: It is located over the fifth intercostal space in the midclavicular line.
- **Lead V₅**: It is located over the anterior axillary line, at the same level as lead V₄.
- **Lead V₆**: It is located over the midaxillary line, at the same level as leads V₄ and V₅.

### 1.2.3 ECG Signal and its Features

![ECG Signal and its Features Diagram](image)

A typical ECG signal is formed by its characteristic waves like, P, QRS and T waves, sometimes it is followed by another wave of small amplitude called U. The generation of different waves, segments and
Introduction

Intervals is associated with respective cardiac phenomena as shown in figure 1.7. P wave is produced by atrial depolarization. The QRS complex is the major positive deflection on the ECG produced by ventricular depolarization. In fact, it represents the timing and sequence of synchronized depolarization of the right and left ventricles.

Actually the QRS complex is formed by Q, R and S waves. The Q wave is not visible in all ECG leads. Physiological Q waves may be observed in leads L_2, aVL, V_3 and V_6 where they represent initial activation of the interventricular septum in a direction opposite to the direction of activation of the main left ventricular mass. R wave is the major positive deflection of the QRS complex. It is upright in most ECG leads except lead aVR where the P wave and T wave are also inverted normally. The S wave is the negative deflection that follows the R wave, representing the terminal portion of ventricular depolarization. In lead V_6, the S wave reflects left ventricular activation while in V_4 the S wave reflects right ventricular activation.

The T wave is produced by ventricular repolarization. It is normally upright in most of the ECG leads with certain exceptions. U waves are occasionally seen in ECG signals after the occurrence of T wave due to repolarization of papillary muscles or Purkinje fibers.

The wave shape, wave amplitude and wave durations are of clinical importance. Apart from that, some intervals and segments are also of great importance for diagnosis purpose. These are also shown in figure 1.8. Typical values of ECG characteristic parameters are given in the table 1.1.

<table>
<thead>
<tr>
<th>Wave duration (ms)</th>
<th>Wave amplitude (mV)</th>
<th>Segment/Interval (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P 110±20</td>
<td>P 0.15±0.05</td>
<td>PR 160±40</td>
</tr>
<tr>
<td>QRS 100±20</td>
<td>QRS 1.5±0.5</td>
<td>QTc 400±40</td>
</tr>
<tr>
<td>T 180±20</td>
<td>T 0.3±0.2</td>
<td>ST 100±20</td>
</tr>
</tbody>
</table>
1.2.4 Noise in ECG Signal

ECG may be accompanied by different kinds of high and low frequency noises generated mainly at the time of recording or transmission. Resulting from different sources, noise may be either of high frequency or low frequency. Depending upon the source, the noises are classified as follows:

(i) Powerline interference: It generates due to the interference of mains supply of the recording system. It may be of 50 Hz or 60 Hz frequency depending upon the quality of the supply. Its amplitude may be up to 50% of peak to peak ECG voltage.

(ii) Motion artifact: This is a low frequency noise generated due to the movement of the electrode from the contact region of the skin of the patient. This noise is prominent for ambulatory patients or in case of injury. Lack of skin contact with electrode generates an abrupt change in impedance and thereby an irregular change in baseline position which makes the measurement of amplitude features a difficult task.

Figure 1.8: Important Features of ECG wave
Electrode contact noise: This noise is generated if the electrode is completely pulled off leading to a sharp change of the recorded voltage at saturation level.

Baseline wander: It originates from respiration and introduces a very low frequency in the baseline of the ECG, which is originally expected to be straight. Generally the baseline noise has frequency 0.15 to 0.3 Hz, but it is a common practice to consider baseline wander frequency up to 0.5 Hz as the lowest frequency content in ECG is 0.67 Hz [24] during slow heart rate.

Electromyographic (EMG) noise: It adds up some potential with original ECG voltage from the electrical activity due to muscle contractions.

Electrosurgical noise: This is a rarely occurring noise comes up from the other medical equipments present nearby for patient care generating high frequency noise of 100 KHz to 1 MHz.

Quantization noise, aliasing or other signal processing errors (hardware or software) may add some noise along with others.

1.3 Historical development of the study of automatic ECG analysis—literature survey

ECG signal analysis is a very useful tool to detect cardiac abnormalities. Conventionally the ECG is recorded in a strip chart through the ECG machine and later it is examined by the experts. In this regard there is a possibility of human error in interpretation of ECG. With the development of Digital Signal processing tools, automatic analysis of ECG becomes a field of research. This leads to better accuracy and reproducibility in comparison to manual analysis and enables the extraction of information which is not readily available. Sometimes ECG is recorded for a longer duration to detect intermittent cardiac abnormalities if any. This generates a large dataset which is difficult to handle manually. In this regard also the automatic analysis finds its application. Moreover, it is required to handle the data automatically if the data compression and transmission is the primary requirement.
1.3.1 Enhancement of Electrocardiogram by noise elimination

It is one of the most visited problems in automatic ECG analysis to eliminate the high and low frequency noises from recorded ECG using digital filtering techniques. Main difficulty to develop a conventional filter for denoising ECG is that the noise frequency spectra is overlapping with the medically relevant frequency spectra of ECG. At the early stage of ECG baseline wander correction, linear filtering method with time-variable cut-off frequency was suggested for offline processing of ECG signals [1]-[2]. This technique was further extended for on line processing of ECG. Digital filtering methods were also proposed for powerline noise elimination [3]-[5]. Some specialized method to isolate ECG from EMG noise is also proposed [6]. But it is really a difficult task to enhance ECG using conventional digital filtering because of the noise frequency lies within the signal frequency range as indicated earlier. Moreover, FIR digital filter needs a large number of coefficients which restricts its use in practice. Adaptive filtering methods are also reported for enhancement of ECG in [7]-[9]. Statistical techniques such as principal component analysis [10], independent component analysis [11]-[12], and neural networks [13] have also been used to extract a noise-free signal from the noisy ECG. Some recent contributions reports some different methods using different techniques like perfect reconstruction maximally decimated filter banks [14], nonlinear filter banks [15], advanced averaging method, [16]-[17], singular value decomposition [18] for denoising ECG. Over the past few years, ECG enhancement techniques based on the wavelet transform have also received a great deal of attention for possessing multiresolution characteristics [19]-[23]. Recently empirical mode decomposition based ECG denoising for both high and low frequency noises are reported in literature [24].

1.3.2 Feature extraction from electrocardiogram

A filtered ECG is suitable for detection of pathological conditions of heart and an automatic technique requires first extraction of clinically relevant features from the clean ECG before diagnosis. History says that computerized analysis of ECG becomes an integral part of medical instrumentation after the use of microcomputers in instruments way back in 1970s [25]. R peak being the most prominent section of ECG signal, R peak or QRS complex detection becomes the entry point in almost all ECG feature extraction assignment. This section is also important for heart rate measurement, arrhythmia and other abnormality detection. Initial QRS detection algorithms were developed for arrhythmia detection during ambulatory monitoring [26].
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It is difficult to detect QRS accurately not only because of the noise present in it, but also due to the physiological variability of QRS complex. It is very popular technique to use R wave slope for detection of R peak and consequently the QRS complex [27]. Normally the derivative of a stipulated region is computed for maximum slope to denote the R peak. This technique became popular after the development of microcomputers, but it suffers from a great disadvantage that any high frequency noise preset in that region is enhanced and may be wrongly detected as R peak. Moreover, a long persistent QRS complex may not be detected because of lower R slope.

A different hardware based technique is made by first derivative approach. A very popular method using this is discussed in [28] where raw ECG is first pre-filtered using bandpass filter of frequency range 5-15 Hz for QRS enhancement and then a derivative and squaring is followed. Finally a moving average integrator locates the QRS regions with adaptive thresholding. This method is implemented in real time using microcontroller. This method is further improved in [29] where decision rules are optimized with a higher speed before classification of QRS region, which improves classification accuracy. Other syntactic approach uses modern techniques like neural network [30], Support Vector Machine [31] etc. to QRS and other features. All these approaches require a pre-designed filter for noise suppression and to isolate QRS complex from other parts of the signal. But ECG is a non stationary signal, therefore, signal frequency is different for different subjects and even for different beats of the same subject. Moreover, frequency band of noise and QRS complex may overlap. [32] uses adaptive matched filtering technique based on artificial neural network (ANN). The low frequencies are modeled by an ANN based adaptive filter and the residual signal is passed through a matched linear filter for the detection of QRS location. The effectively of this technique reduces due to the variability of QRS complex for different beats of the same subject.

Considering all these disabilities of conventional methods, a signal decomposition based technique is also introduced for detection of characteristic points of ECG signal based on wavelet transform. Wavelet transform can identify and characterize local regularities of a signal by decomposing the signal into its elementary building blocks which are specified in time and frequency [33]. Thus application of wavelet transform eliminates the problem of selecting a specific cut off frequency by reconstructing component wave of interest using suitable coefficients as discussed in [34]-[35] for detection QRS complex, P wave and T wave. One of the disadvantages of wavelet based approach is that there is a requirement of predefined wavelet function prior to decomposition irrespective of the pattern shape. Some other complex
Conclusion
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mathematical approaches using Fuzzy-hybrid neural network, Hidden Markov Model, Hilbert transform etc. are elaborated in [36]-[39]. Very recently a fully data driven technique called Empirical Mode decomposition is used to detect the time domain ECG features [40]-[41]. This approach appears to cater almost all kind of ECG signals due to its adaptive nature.

A few specialized algorithms are also proposed for detection of T and U wave or event detection like T wave offset and alternan [42]-[43]. It is mostly required for QT interval detection to identify ventricular arrhythmias as it indicates ventricular repolarization time. Abnormal QT values have been associated with ventricular pro-arrhythmicity [44]-[46].

1.3.3 Classification of electrocardiogram

Automatic classification of electrocardiograms provides an assistive technology for cardiac abnormality detection and monitoring. Heartbeat analysis, heart rate variability (HRV), Cardiac Arrhythmia and fibrillation, ischemia, infarction, sleep apnea etc. are some of the popular diseases that are addressed by biomedical researchers through several algorithms based on distinctive features. Heartbeat classification is a tool for arrhythmia classification as many arrhythmias manifest as sequence of heartbeats with unusual timing or ECG morphology. Time – frequency based features, ECG morphology and heartbeat interval features are used for heartbeat classification [47]-[48]. A patient adaptive technique for the same is proposed in [49]. Some arrhythmias such as atrial fibrillation (AF) may be tolerated than others such as ventricular tachycardia (VT) and ventricular fibrillation (VF) which are life threatening [50]. Hence a number of researches have made for automatic classification of these specific arrhythmias. Almost all methods require QRS and other features extraction followed by the design of a suitable classifier. A high order spectral analysis technique is illustrated in [51] for quantitative analysis and classification of arterial and ventricular tachyarrhythmia. In this method the bispectrum is estimated using an autoregressive model, and the frequency support of the bispectrum is extracted as a quantitative measure to detect the abnormalities. The technique shows 83.3% sensitivity and 100% specificity for arterial fibrillation detection and 81.8% sensitivity and 90.9% specificity for ventricular tachycardia analysis. A time-frequency based approach for VF detection using instantaneous mean frequency is proposed in [52].

A number of beat detection techniques for arrhythmic beats are also reported in literature. Some earlier method [53] for identification of premature ventricular contraction (PVC) involves detection and delineation of QRS complex by first difference of digitized ECG. Then the linear discrimination function is
obtained based on the features like minimum phase and signal length. In [54] PVC beat detection technique is discussed using Hidden Markov Model with 87.20% selectivity and 85.64% positive predictivity. Another method using wavelet based and timing interval features is proposed in [55] decision is taken by ANN based classifier for robust detection of PVC. The accuracy was 95.16% over one set of data and 96.82% over another set of data taken from MIT-BIH Arrhythmia database. A dynamic model-based method [56] is also proposed using extended Kalman filter for PVC detection with average detection accuracy of 99.10%, aggregate sensitivity of 98.77%, and aggregate positive predictivity of 97.47% using the same database. Another kind of arrhythmic pattern occurs due to blockage in bundle of His which resists the conduction of cardiac rhythm. Automatic methods are also used for detection of this event as reported in [57]- [58].

Heart rate variability is the indication of rhythmic disorder and can be used as a predictor of mortality after Myocardial Infarction [59]. Hence it became a point of attraction for researchers for long. Several authors have suggested automated strategies for inferring heart rate and other statistics from recordings of the full ECG waveform or from the complete sequence of inter-beat intervals [60], [61]. A large scale analysis in noisy environment is presented in [62] using unsupervised clustering followed by Bayesian regression of the heart rate data.

Myocardial ischemia and infarction is the condition where oxygen deprivation to the heart muscle is accompanied by inadequate removal of metabolites due to reduced blood flow. Most prominent features that changes due to these conditions are ST segment alignment and T wave texture. Several techniques that evaluate the ST segment changes and the T-wave alterations by different methodologies have been proposed for ischemic beat detection. More specifically, the use of approaches like wavelet theory [63], set of rules [64], artificial neural networks [65]-[67] and genetic algorithms [68] have been previously reported. Neural network based methods are the most common technique with good performance but they do not provide explanations for the classification decisions. Rule-based approaches exhibit the highly desirable feature of interpreting the decisions but their performance is reduced. Classification of arrhythmia with rule mining based associative rule is also proposed [69] with high classification accuracy. Another research [70] addresses the problem to comment on the size and location of ischemic region from ST segment shift. In recent times a number of researches have been carried out for real time analysis of ECG patterns [71]-[75] to detect the abnormalities at the time of its onset. Nowadays the implementation of
predictive models through the use of AI methods has become an important approach for ECG classification. Many solutions based on this approach have been proposed. Some of the best known techniques are the multilayer perceptron [76], self-organizing maps [77], learning vector quantization [78], linear discriminant systems [79], fuzzy or neuro-fuzzy systems [80], support vector machines [81], and the combinations of different neural-based solutions, so-called hybrid systems [82]. A review of ECG pattern recognition and classification using different linear and non-linear methods including neural network is explained in [83].

1.3.4 Application of electrocardiogram for biometric analysis

Though ECG is extensively used as a tool of cardiac abnormality monitoring and detection, research has been conducted to verify the applicability of ECG as a biometric trait nowadays because of the fact that it is difficult to mimic the pattern of ECG. So it can act as a reliable and foolproof parameter for authentication. Recently some research has made to test the applicability of ECG as a biometric feature. Arguably Biel et al. [84] were the first to report the possibility of ECG to be used as a biometric. They have conducted the biometric experiment on ECG recorded from a group of 20 subjects. A set of amplitude and temporal features were extracted from each record for identification of a person in a predefined group. Feature set is dimensionally reduced by correlation matrix. Another investigation [85] shows the feasibility of one lead ECG as a new biometric for identity verification. The experiment has been conducted on 20 individuals on seven features, extracted from mainly QRS complex. Using the techniques of neural network and template matching the experiment of human identity verification has been performed. An ECG based identification system using only temporal features is also introduced [86]. In this procedure an input ECG was filtered to eliminate the effects of noise and the signal's peaks were detected in the time domain by finding local maxima in the regions surrounding each of the P, R and T complexes. Then, 15 features were extracted that denote the time distances between detected features. Wilks' Lamda was used for feature selection and linear discriminant analysis (LDA) was used for classification. A technique based on heart rate variability and some other temporal features is also reported [87] with only a group of five subjects. A QRS complex based approach with its $4^{th}$ order Legendre Polynomial as the signature is also available [88] with good accuracy. Methods using fiducial points and without fiducial points by AC/DCT technique are introduced [89] for two groups with 13 subjects in each. Classification is done based on LDA and neural network
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based technique. In AC/DCT method similarity between the subjects is measured based on normalized Euclidian distance and a nearest neighbour is used as the classifier. But this ECG morphology based approach may fail when appearance of two ECGs are similar. A wavelet distance measurement technique for classification of 50 subjects achieved accuracy 89% as explained [90]. In [91] a technique for person identification by making the classification based on the similarities and dissimilarities on electrocardiogram phase space is elaborated. A PCA/LDA based approach is also suggested [92]. Most of the methods require detection of characteristic points of the ECG signal for feature extraction. A different approach with non-fiducial feature based technique is reported in [93] using spectral coefficients computed through linear predictive coding (LPC) and classification is done using neural network based approach. Double fold approach is proposed in [94] where the parameters of the pulse active ratio (PAR) feature vector are represented by a four digit PIN no. Authentication is made for 20 subjects first by verifying the PIN no. and finally by ECG features vector matching.

1.4 Motivation and Goal

ECG is one of the most important physiological signals that is studied, analyzed and used for diagnosis purposes. It is commented by WHO (World Health Organization) that cardiac diseases are the prime cause of death in the world and the probability of death due to heart related reason will be increased in future. The problem is more intensive in the third world countries like India because of the scarcity of medical persons, monitoring systems, medical centers and lack of proper communication and transport systems for the patients especially in the rural areas. General awareness regarding the cardiac complexities and related treatments is also very poor in these areas.

In this scenario an assistive technology for basic diagnosis of cardiac abnormalities may help the medical persons to detect the irregularity easily at the earliest. Moreover, a computerized automatic continuous monitoring system can help in intensive cardiac care units (ICCU) by reducing the time required for interpretation as well as human effort.

In Holter monitoring, the long term continuous ECG signals are first digitized and then compressed and stored in hard storage device. This data is later uncompressed and analyzed by medical personals to detect abnormalities. The analysis of this data takes a substantial time and automation in analysis considered being a promising one.
With the development of digital computers from microcomputers, automation in biomedical domain becomes easier and a number of algorithms are proposed, explained and used. The outlined recent progress in the techniques of processing and classification of ECG signals in the perspective of overall development of cardiac patient care has inspired to carry out this research work. The limitation of conventional techniques of ECG filtering, data analysis and feature extraction is non-stationary nature of the data. Again, classification and detection technique should be able to identify the patient’s condition very early and thus the system should be very fast. The primary goal of this thesis is to overcome the limitations of conventional ECG signal processing methods by making it fully adaptive and to construct a fast classification system to assist cardiologists for patient care and monitoring. Finally the thesis also discusses the probability of use of ECG for human authentication in biometric system which as well as helps in monitoring a group of patients without human intervention and extra data processing for automation.

1.5 Brief overview of contribution

The principal contributions of thesis are as follows:

- Problem of selecting a specific cut-off frequency in case of conventional filter for ECG feature extraction is eliminated using wavelet transform.
- Problem of requirement of a basis function a priori in wavelet transform is overcome by developing an algorithm using empirical mode decomposition technique for ECG filtering and feature extraction.
- A fast ECG arrhythmia classification technique is developed using by incorporating binary logical classifier.
- Possibility of the use of ECG as a biometric parameter is investigated and an algorithm is proposed to enhance the authentication accuracy by data modeling.

1.6 Organization of the thesis

The thesis has been organized as follows:
Introduction

• Chapter 1: Introduction – In this chapter, basics of the construction and functioning of heart, ECG features, development of automatic ECG analysis, motivation and contribution to the thesis are discussed. Dataset used for the experimental study and the machine specification are also furnished in this chapter.

• Chapter 2: ECG analysis by wavelet transform – A time frequency based approach for ECG signal processing and feature extraction is presented in this chapter. The essence of time frequency based analysis and the performance of the technique are presented in this chapter.

• Chapter 3: ECG Enhancement and Feature Extraction by Empirical Mode Decomposition – The limitation of wavelet based approach that the requirement of a basis function a priori is solved by using empirical mode decomposition method. In this technique the basis function is derived from the signal itself and hence the method is fully adaptive. ECG noise elimination and feature extraction procedures and performance of the algorithms are described in this chapter.

• Chapter 4: Classification of ECG signals – Automatic classification techniques using supervised classification rule, artificial neural network and binary logical classifier are presented in this chapter. Diseases like myocardial infarction, cardiac arrhythmia are considered for detection. Among a number of arrhythmic beats premature ventricular contraction, bundle branch block and paced beat are considered for classification using the proposed method. Binary logical classifier is a novel approach to detect arrhythmic beats using time domain features. The results and performance indices are also incorporated in this chapter.

• Chapter 5: Potential of ECG to be used as a biometric parameter is explained in this chapter. It is shown that a curve fitting technique after principal component analysis improves the detection accuracy of subject for a small population.

• Chapter 6: Conclusion and future scope – In this chapter overall conclusion of the thesis is presented and the possible future research directions are indicated.
Two different data sets from physionet data bank [95] are used in this thesis.

- **PTB diagnostic ECG database**

PTB (Physikalisch-Technische Bundesanstalt) diagnostic ECG database (ptb-db) is provided by the National Institute of Germany. It contains 549 records from 290 subjects with the age varies from 17 to 87 years and there are 209 male and 81 women subjects. Each record has conventional 12 leads ECG measurement along with three Frank leads – Vx, Vy and Vz simultaneously. Each signal is digitized at 1000 samples per second, with 16 bit resolution over a range of ±16.384 mV. The clinical history and diagnosis is also provided for most of the subjects as below:

<table>
<thead>
<tr>
<th>Number of subjects</th>
<th>Diagnostic class</th>
</tr>
</thead>
<tbody>
<tr>
<td>52</td>
<td>Healthy Control</td>
</tr>
<tr>
<td>148</td>
<td>Myocardial Infarction</td>
</tr>
<tr>
<td>15</td>
<td>Bundle Branch Block</td>
</tr>
<tr>
<td>18</td>
<td>Cardiomyopathy/Heart failure</td>
</tr>
<tr>
<td>14</td>
<td>Dysrhythmia</td>
</tr>
<tr>
<td>7</td>
<td>Myocardial hypertrophy</td>
</tr>
<tr>
<td>6</td>
<td>Valvular heart disease</td>
</tr>
<tr>
<td>4</td>
<td>Myocarditis</td>
</tr>
<tr>
<td>4</td>
<td>Miscellaneous</td>
</tr>
<tr>
<td>22</td>
<td>Not available</td>
</tr>
</tbody>
</table>

- **MIT-BIH Arrhythmia database**

This database is prepared and circulated by Boston’s Beth Israel Hospital (now the Beth Israel Deaconess Medical Center) and Massachusetts Institute Technology since 1980. The database contains 48 numbers of 2 channel 30 minute records of arrhythmia patients. Each recording is digitized with 360 Hz sampling frequency with 11 bit resolution over a 10 mV range. The subjects were 25 men aged 32 to 89 years, and 22 women aged 23 to 89 years. In most records, the upper signal is a modified limb lead I (MLII), obtained by placing the electrodes on the chest. The lower signal is usually a modified lead V1 (occasionally V2 or V5, and in one instance V4); as for the upper signal, the electrodes are also placed on the chest.
1.8 Machine Specification and Software

All the algorithms proposed in this thesis are implemented in MATLAB 7.1 [96] on Microsoft Windows XP running on a PC with system configuration Intel Core 2 duo processor (centrino) of speed 3.06 GHz with 2 GB of RAM.