CHAPTER 1

INTRODUCTION

1.1 GENERAL

The Electrocardiogram (ECG) signal is an electrical recording of the cardiac activity, which is indicative of the status of the heart. A cardiologist can correctly interpret heart disorders by observing the duration and amplitude of the PQRST complexes along with the morphology of the ECG waveform. In giving interpretation, the cardiologists take into consideration information such as patient history, heart rate, shapes of QRS complex, and other more subtle features. Such interpretations by a cardiologist backed by clinical knowledge and experience are indispensable in providing a complete diagnosis.

Computers effectively assist a cardiologist in the task of ECG monitoring and interpretation. The automation of the diagnostic process has been made possible by computerized procedures which are capable of duplicating the observations and decisions of the experts. This kind of applications were first formulated in a small way in the late 1950s, while today several commercial application programs are processing several million ECG records per year.

The most prevalent automated approach to electrocardiographic diagnosis follows a diagnostic tree, much in the same way that the clinician approaches diagnosis. The use of automated ECG classification has been on the increase because the diagnostic quality is comparable to that of expert diagnosticians. An estimated 20% of global clinical electrocardiography
involves the use of the computer. An attractive feature of such automated diagnosis is the consistency in the diagnostic reports of the same record on successive evaluations.

1.2 TECHNIQUE OF ELECTROCARDIOGRAPHY

The electrical activity generated by the heart can be modeled as a dipole source, symbolically shown as a cardiac vector placed inside the thorax (Figure 1.1). An electrode pair on the body picks up the projection of that cardiac vector onto the body surface. The ECG is recorded by placing several electrode pairs on the body. It is now a common clinical practice to record ECGs from 12 leads; three bipolar limb leads connected to the arms and legs, designated I, II, III; three augmented leads derived from the limb leads aVR, aVF, aVL and six unipolar precordial or chest leads V1, V2, V3, V4, V5, V6 (Figure 1.2). The origin of recording from limb electrodes may be attributed to the historical work by Einthoven. He specified the three limb leads as parts of an imaginary triangle, the 'Einthoven triangle', with the heart at its center.

The simplified block diagram of analog recording of electrocardiogram given in Figure 1.3, includes the electrodes (along with electrode jelly or paste), lead wires, preamplifiers and recording equipment. Electrodes for use at the extremities are concave silver plates 3.5 x 5.0 cm in size. Precordial measurements are often made with an electrode shaped like a suction cup (4.75 cm in diameter) and attached to a rubber suction bulb. The electrode, before application, is covered with an electrolyte jelly to reduce electrode-skin resistance.

The electrocardiogram detected by electrodes may be corrupted with noises and artifacts due to electrical interference, patient respiration, patient movement and muscle tremors. The corresponding artifacts in ECG are known as Powerline frequency (AC) interference, Baseline wander.
Figure 1.1 A model of the cardiac vector
Figure 1.2 ECG lead configurations
Figure 1.3 Block diagram of ECG recording
Motion artifacts and Muscle noise respectively (Figure 1.4). Among these artifacts, the muscle noise can be avoided by selecting proper site for the electrode placement and the motion artifacts can be avoided by educating the patient. The other two noises, namely powerline (AC) frequency interference and baseline wander in ECG are unavoidable and hence must be removed before doing any analysis on ECG waveforms.

The powerline interference of 50 Hz (60 Hz in some countries) noise in ECG is caused by two types of pickups, namely electrostatic (capacitive) pickup due to the existence of capacitance between the human body and the nearby powerline, and magnetic (inductive) pickup due to loops formed by the leads connected to the human body. Since this powerline interference is normally in the order of 0.8 mV (typical value) which is comparable to the amplitude of ECG signal, care must be taken in reducing this interference. Even though appropriate shielding and twisted wires are used to minimize this noise, the use of 50 Hz notch filter is helpful in removing the powerline interference. But the analog version of this notch filter may adversely affect the signal following rapid changes in the ECG due to ringing.

The baseline wander artifact in ECG, due to the direct or indirect effects of patient respiration or as a result of slow electrochemical changes at the electrode-skin interface, has the frequency spectrum in the range of 0 to 0.2 Hz (typical). In analog recorders highpass filter of very low cutoff frequency is used to avoid baseline wandering in ECG. The use of analog highpass filter poses some problems in the form of phase distortion. Most standards (American Heart Association, AHA; American National Standard Institute, ANSI) specify a lower cutoff frequency of 0.05 Hz and upper cutoff frequency of 100 Hz for the ECG amplifier. To avoid serious system distortion, the amplifier must be linear (constant gain independent of input signal strength). The AHA requirement is that for low-amplitude signals (<0.5 mV) the deviation from linearity should be less than 0.025 mV.
Figure 1.4 Common types of noises in ECG waveforms

(A) Motion Artifact

(B) Baseline wander

(C) Muscle noise

(D) Powerline interference
For signal amplitudes between 0.5 and 5.0 mV the deviation from linearity should be under 5%.

The use of computers in electrocardiography facilitates the introduction of many better methods in powerline noise removal and baseline wander in ECG than those of analog methods. In addition to this, it opens the ways for automated ECG analysis and classification.

The computerized ECG system may be visualized to have three functional blocks as shown in Figure 1.5.

![Figure 1.5 Functional Blocks in Computerized ECG System](image)

The 12 lead signals are digitized by a data acquisition system and the digitized data are supplied to the computer. To ensure the integrity of the digitized signal, a sampling rate of 500 Hz with 12 bit resolution are recommended.

Preprocessing is essentially done for the removal of powerline interference and baseline wander in ECG signals. After the preprocessing of ECG, the function of the next stage, as in Figure 1.5, is the representation of electrocardiogram and its analysis. Increasingly, digitized electrocardiographic signals are transmitted elsewhere and/or stored for
later display and analysis. Particularly where signals picked up by multiple leads are recorded in separate channels simultaneously and time-multiplexed for transmission, the data rates may become quite high. Problems can arise in handling this high data rate or in the sheer volume of data that must be stored. For these and other reasons data compression techniques are invariably adopted.

Classification using electrocardiograms deals with either Arrhythmia classifications based on rate (bradycardia, tachycardia, etc) or classification of disorders based on morphology (hypertrophy, infarction etc) or pattern classification of ECG complexes (eg. QRS complex).

1.3 REVIEW OF PREPROCESSING, ANALYSIS AND CLASSIFICATION

Powerline interference (whether 60 Hz or 50Hz) is a significant source of noise in biomedical signal recording. Earlier, analog circuits have been used for signal conditioning of electrocardiograms. As an alternative, algorithms implemented as programs on microprocessors can do similar filtering tasks. Ahlstrom, M.L. and Tompkins, W.J. (1985) report on an adaptive 60 Hz filter for ECG signals that uses an internally generated reference signal. John R. Glover, Jr. (1987) shows that Ahlstrom and Tompkins filter is approximately equivalent to a nonadaptive second order notch filter, implying that the performance of a nonadaptive 60 Hz notch filter and an adaptive 60 Hz notch filter with an internally generated reference are equivalent. As the transient response time of a notch filter increases, the rejection bandwidth of the filter decreases. If an adaptive 60 Hz notch filter is adjusted to adapt quickly to changes in noise, the rejection bandwidth will be wider and there will be more attenuation in signal components at frequencies close to 60 Hz. Conversely, if the bandwidth of the notch filter is reduced, the transient response time will increase and the filter will adapt more slowly to changes in noise.
Elimination of powerline interference in the ECG by adaptive filtering, using an external reference signal was first proposed by Bernard Widrow et al., (1975). In Widrow’s adaptive filter, the primary input is taken from the ECG preamplifier; the 60 Hz/50 Hz reference input is taken at a wall outlet. The adaptive filter contains two variable weights, one applied to the reference input directly and the other to a version of it shifted in phase by 90 degrees. The two weighted versions of the reference are summed to form the filter’s output, which is subtracted from the primary input. Selected combinations of the values of the weights allow the reference waveform to be changed in magnitude and phase in any way required for cancellation. The two variable weights are required to cancel the single pure sinusoid. John R. Glover, JR (1977) has extended this adaptive noise cancelling technique to sum of sinusoids as the reference to eliminate multiple-sinusoid interference. As long as the reference is available that includes every sinusoidal interference, the adaptive noise canceller will automatically create a notch over each sinusoid and follow it if it drifts in frequency. Nitish V. Thakor and Yi_Sheng Zhu (1991) suggest the use of true interfering signal as a reference instead of taking the reference from wall outlet as reported by Widrow et al., (1975). The common-mode signal, usually taken from the right leg reference electrode, is truly correlated with the noise in the ECG recording. The primary input to the filter is the ECG signal to be filtered, and the reference input is the common-mode signal.

Mohammed Ferdjallah and Ronald E. Barr (1994) investigate adaptive digital notch filters for elimination of powerline noise from the biomedical signals. The adaptive process is considerably simplified by designing the notch filters by pole-zero placement on the unit circle using some suggested rules. A constrained least mean-squared algorithm is used for the adaptive process. In this literature, three types of adaptive notch filters are discussed. For the first case, an adaptive FIR second order digital notch filter is designed to track the center frequency variation. For the second case, the zeros of an adaptive IIR second order notch filter are fixed
on the unit circle and the poles are adapted to find an optimum bandwidth to eliminate the noise to a predefined attenuation level. In the third case, both the zeros and poles of the adaptive IIR second order filter are adapted to track the center frequency variation within an optimum bandwidth.

Jiapupan and Tompkins, W.J. (1985) develop a real-time algorithm for detection of the QRS complexes of the ECG signals and implement it in Z80 assembly language. A bandpass filter of desired passband 5-15 Hz with a combination of lowpass and highpass filters preprocesses the signal to reduce the interference such as baseline wander and 50 Hz/60 Hz powerline interference. Since the application is to detect the QRS complexes, the bandpass filter of passband 5-15 Hz acts as a preprocessing filter.

Soo-Chang Pei and Chien-Cheng Tseng (1993) investigate a new second order IIR adaptive notch filter algorithm based on the least mean p-power (LMP) error criterion to cancel 60 Hz interference in the recording of electrocardiograms. The performance of this adaptive algorithm with $p=1$ is shown to be better than that of conventional least mean square (LMS, $p=2$) algorithm in cancelling 60 Hz powerline interference in electrocardiograms.

Mohammed Ferdjallah and Ronald E. Barr (1990) investigate frequency domain methods for the removal of powerline noise from ECG signal. The aim of their approach is to remove the powerline noise without affecting the ECG frequencies where the powerline noise occurs. A local processing method is applied to a set of frequencies in the vicinity of the powerline frequency of 60 Hz (say 50 Hz to 70 Hz) after the Fourier transform of the noisy ECG is computed. One important condition for the selected frequency set is that the powerline noise frequency value must be the biggest spike in the spectrum of the set (50 to 70 Hz). If the largest frequency value in the set is not at the powerline frequency, the process may not converge.
Levkov, C. et al., (1984) suggest a method of subtracting 50 Hz interference from the ECG. The 50 Hz interference is measured in intervals of the ECG signal, where the interval is isoelectric or changes linearly with time. To find an isoelectric or linear segment of the signal regardless of the superimposed interference, a criterion is used. It is shown that the interference values are computed using the nearest possible samples to the ones where the subtraction takes place. Once the interference values are found, they are subtracted from the original signal. This method requires a sampling rate which is a multiple of the interference frequency (F) and makes use of the fact that the sum of equally spaced interference sample amplitudes in one period, T=1/F, is zero. Christov, I.I. and Dotsinsky, I.A. (1988) modify this approach to overcome the problem arising when the sampling rate is an even multiple of the interference frequency.

In the powerline interference subtraction method (Levkov, C. et al., 1984; Christov, I.I. and Dotsinsky, I.A. 1988), the frequency and amplitude of interference are assumed to be approximately constant. Thus, a group of interference values obtained from the last linear sampled segment can exactly replace the groups of interference values of the following non-linear sampled segments of ECG. However, the frequency of actual interference always deviates from 50 Hz. Although the drift is slight, it is enough to make significant errors in the replacement when the interference amplitude is relatively large. This kind of error can be reduced if the groups of interference values of the non-linear sampled segments are replaced by a dynamic amendment of the most recently obtained interference values. Yan X.G, (1993) improves this approach by estimating the interference values of the non-linear sampled segment from the interference values of the linear segments of ECG. Subtraction of this estimated interference values of the non-linear sampled segments from the non-linear segments of the ECG reduces the error.
Eckehart Cramer, et al., (1987) investigate a method to remove 50/60 Hz noise by estimating the powerline signal amplitude and phase from the entire digital ECG cycle, and incorporating this estimate into a filter. In this method the powerline interference is treated as the signal of interest and the remaining ECG content as transient noise. The estimated powerline interference is subtracted from the original ECG.

As stated in the literature, (Eckehart Cramer, et al., 1987), the ideal powerline interference filter ought to be (1) narrowly selective, removing the noise without removing other signals at nearby frequencies, (2) sensitive to a range of frequencies over which this noise is known to spread, (3) effective in removing the higher frequencies of the powerline interference frequencies, also (4) equally valued within a wide range of sampling frequencies, (5) independent of any baseline drift, and ought to leave baseline undisturbed, (6) impervious to high amplitude signals (e.g., QRS complex) with frequency content less than the powerline frequency, (7) insensitive to the presence of isolated higher order dropouts, (8) sensitive and self adjusting to both slow and abrupt changes in the amplitude and frequency of interference, (9) implementable in real time form, (10) requiring minimal computer storage, (11) of low computational complexity, (12) needing minimal computational time. No one can design a filter that meets all these criteria. Certainly some properties are mutually exclusive. Each actual filter has its particular strong and weak points among these ideal requirements.

Meyer, C.R. and Keiser, H.N. (1977) describe a fast and elegant technique for the computation of a third-order polynomial through consecutive PR segments. This cubic spline technique gives a rather good estimation of the baseline wander in normal ECG recordings. The method assumes that the PR segments are well defined, recognizable and that their position is known. The baseline wander noise is reduced by simply subtracting the estimate from the raw data (ECG with baseline wander).
Low frequency heart activity is unaffected by this process since such activity is not admitted into the baseline estimate and hence cannot be subtracted from the raw data. When the baseline sampling frequency is four times higher than a baseline noise frequency component, more than 88% of that noise component is removed (i.e., at a resting heart-rate of 60 beats/minute, baseline noise components at 0.25 Hz are effectively removed; and at an exercise heart rate of 150 beats per minute, baseline noise components up to 0.6 Hz are effectively removed without affecting ST segments). Since the estimates are subtracted abruptly from the ECG, it is possible to get error in the skeletal waveshape especially when the PR knots are taken at improper location.

A useful method for removing baseline wander in real time is the application of digital linear phase filtering (Van Alste, J.A., et al., 1986). Baseline wander is removed effectively in real time using a fixed low cut-off frequency of 0.8 Hz. In 1975, the American Heart Association recommended that the frequencies as low as 0.05 Hz should be preserved to avoid ST segment distortion. Hence any attempt to suppress the baseline wander using highpass filtering resulted in 'smearing' of the QRS complex into the ST segment. This problem due to highpass filtering has been studied by Christov, I.I. et al., (1992). They suggested a method in which the ECG signal, excluding the QRS complexes, is lowpass filtered by an averaging filter and the signal thus obtained is subtracted from the original.

Sornmo, L. (1993) investigates filtering approach to provide better suppression of baseline wander in ECG. Time-varying filtering techniques are applied for correction by letting the cut-off frequency of a linear filter be controlled by the low frequency properties of the ECG signal. The time-varying filter is implemented as a bank of linear lowpass filters, in which each filter has a slightly differing cut-off frequency. The idea is to adapt the cut-off frequency of the filter to the current 'level' of baseline wander in the signal. If no baseline wander is present, the filter with the
lowest cut-off frequency is used and so on. The adaptation is related to the
error between the output of the currently selected filter and that of the filter
with the highest cut-off frequency. The major drawback of this method is
that the initial heart rate estimate should be determined in order to get true
estimate of the baseline wander which is to be subtracted from the actual
signal (ECG with baseline wander).

Van Alste, J.A. and Schilder, T.S. (1985) suggest an approach of
digital filtering used to eliminate both baseline wander and powerline
interference from the ECG. A linear phase filter is designed with desired
frequency spectrum of small stop-band notches at 0 Hz, 50 Hz and at its
higher harmonics to remove powerline frequency disturbances.

bandpass filter to extract the 50 Hz, 100 Hz and baseline wander (at 0 Hz)
interferences. A sharp notch filter is implemented by subtracting the output
of bandpass filter from the noisy ECG signal. This method dictates that the
bandpass filter be a linear phase FIR filter and also the sampling frequency
an integer multiple of the powerline frequency. This method uses spectral
frequencies subtraction and hence while subtracting the output of the
bandpass filter at 50 Hz, the spectral component of ECG at 50 Hz is also
subtracted.

compression algorithm using second difference method. The digitized ECG
signal is manipulated under second difference operation to generate a
residual. The residuals are coded with Huffman coding method after the
residual error is corrected for truncation error. An average compression ratio
of about 22.28% (4.5:1) with a mean square error of 0.00019 is reported.
Sateh M.S. Jalaleddine et al., (1990) discuss elaborately the various
techniques of ECG data compression. ECG data compression techniques are
presented in two major groups; direct data compression and transformation.
methods. The comparison of some ECG data compression schemes in terms of their compression ratio, sampling frequency, percent RMS difference (PRD) and wave recognition are presented. The authors conclude with the presentation of a framework for evaluation and comparison of ECG compression schemes.

Tai, S.C. (1992) investigates a new real-time ECG data compression algorithm known as CORNER. The results of this new algorithm are compared with those of AZTEC (Amplitude Zone Time Epoch Coding) algorithm. The author reports that an average value of SNR (RMS error) of 27 dB (5.668) is achieved even at an average bit rate of 0.79 bit/sample by employing CORNER algorithm, whereas the average value of SNR (RMS error) achieved by AZTEC under same bit rate is 16.6 dB (19.368).

Gil Nave and Arnon Cohen (1993) suggest a parameter extraction method based on linear prediction coding (LPC). In the conventional LPC method (short-time prediction, STP), the n\textsuperscript{th} sample of a signal is predicted by its past samples. But in this long-term prediction method (LTP), the n\textsuperscript{th} sample is predicted using samples of past beats using the fact that ECG signal has a quasi-periodic nature. In LTP method, the PRD error at 250 Hz sampling frequency is lower than that of STP at any bit rate.

Brian Bradie (1996) investigates a wavelet packet based algorithm for the compression of single lead ECG. This algorithm claims a compression ratio of 21.4:1 at an average data rate of 184.7 bits per second with excellent reconstructed signal quality. Compared with the application of the Karhunen-Loeve (KLT) transform method, the wavelet packet method, on an average, produces 25% lower data rates and requires less than one-third execution time.

Gustavo Belforte et al. (1979) investigate a methodology for automatic processing of ECG waveforms based on syntactic algorithms.
this method, the sequences of the energy peaks of the derivatives of the ECG waveforms corresponding to different leads are coded into string of messages with a very simple look-up table. A string that may correspond to a QRS complex is called QRS hypothesis. In the recognition process, a grammar, derived from samples that always appeared with true QRS complexes during learning, transforms QRS hypothesis into QRS events. The error rate in the QRS detection depends on the threshold value fixed to identify the energy peaks of the ECG waveform derivative.

Kenneth P. Birman (1982) propose a rule based approach to ECG analysis using a waveform comparison strategy. In this method, QRS complex recognition involves two levels of signal analysis; R-wave detection and R-wave morphology interpretation. Each QRS morphology is modeled as essentially unipolar R-wave or bipolar R-wave or notched R-wave and is represented using rule activation which measure the slope and approximate amplitude of the QRS complex. The major drawback of this method is the unnecessary calculations when several morphologies symbolically match a QRS complex and hence computational cost is more.

Skordalakis, E. (1986) describes in his review paper of syntactic ECG processing about the various primitive patterns, pattern grammar and purpose handled by different investigators. The various effects of syntactic ECG processing lead to peak recognition, QRS detection, arrhythmia detection and formal description of normal ECGs. The complete problem of the recognition of the electrocardiographic patterns and the measurement of their parameters by the syntactic method has not yet been solved.

Ewa Pietka (1991) investigates an improved syntactic approach to extract feature from ECG signal. The algorithm consists of four procedures; namely P procedure, Q procedure, QRS procedure and PR procedure to find the on-set and off-set values of the segments. The average correct evaluation rate of QRS complex falls between 85% and 87%.
Quin-Lan-Cheng et al., (1987) propose an algorithm to recognize various kinds of QRS morphologies from ECG signals. From a set of significant points which characterizes the ECG waveform, the pattern matching algorithm detects and classifies QRS complexes in three major steps. First, R-waves of ECG are detected from the analysis of global curvature; second, the morphology of the QRS complex is determined; third, QRS complexes with different morphologies are classified by a correlation algorithm. This method is prone to error in cases of ECG signals from patients with relatively frequent and unstable arrhythmias.

Quizhen Xue et al., (1992) investigate an artificial neural network based adaptive matched filter (whitening filter) for QRS detection of very noisy ECG signals. The input ECG signal is first preprocessed by an adaptive noise removal filter based on artificial neural network (ANN) and then it is applied to matched filter for QRS detection. The QRS template used for matched filtering is updated by an ANN recognition algorithm, which provides better adaptation to signal changes than other matched filter techniques.

Niranjan, V.C. and Murthy, I.S.N. (1992) describe a simple method based on repetitive scanning of the Z-plane of the discrete cosine transformed ECG signal by the chirp Z transform technique to measure R-R interval and locations of component waves and isoelectric regions, in addition to a data compression of 10 : 1. The data compression is achieved by representing the ECG signal samples in terms of pole-zero pairs.

In the detection of QRS complexes, an algorithm based on wavelet transform is developed by Cuiwei Li et al., (1995). By using this method, the authors claim QRS complex detection rate of 99.8% for the MIT/BIH database. The distinct feature of this method is that it is easy to characterize the ECG waves with multiscale information and also the QRS complex can be distinguished from high P and T waves, baseline drift and
noises in ECG. The detection of onset and offset of the P and T waves in ECG using a different mother wavelet method is reported by Sahambi et al., (1996).

Laguna, P. et al., (1996) investigate an adaptive system based on the Hermite functions to estimate and track the QRS complex features in the ECG signal. This system provides better signal to noise ratio at the estimation than in the direct method of estimation.

The Hermite model parameters have been used as features for QRS classification and data compression of the ECG by Jane et al., (1993). A compression ratio of 10 : 1 on ECG records from MIT/BIH data base has been obtained.

The use of artificial neural network for classification of ST-T abnormalities of the electrocardiogram is investigated by Devine and Macfaraine (1993). Only the leads I, aVL, V5 and V6 are considered. ST-T segments in these leads are visually classified by an experienced electrocardiographer as LV (Left Ventricular) Strain or not. The result shows that the neural network has higher sensitivity than the method based on conventional criteria (97 % against 89 %).

1.4 OBJECTIVE OF THE THESIS

The main objective of this thesis is to investigate and report on the application of Artificial Intelligence (AI) techniques in Preprocessing, Representation and Analysis, and Classification of electrocardiograms. In the preprocessing of electrocardiograms, rule-based approach and also genetic algorithm method are applied for the removal of 50 Hz powerline interference noise in ECG. Also, in the removal of baseline wander in ECG, LMS adaptive algorithm with estimated reference input is investigated.
Representation of electrocardiograms with a sophisticated data structure, called a complete tree results in not only data compression of ECG but also helps to analyze the ECG by doing basic essential measurements such as the peak amplitude of complexes P, QRS and T, and also the interval measurements. Further, feature samples of ECG are obtained through tree representation of normal and abnormal (Anterior wall Myocardial Infarction, Left Ventricular Hypertrophy) electrocardiograms. In this way, tree representation of ECG offers three advantages, namely, data compression, basic analysis and feature extraction for classification. Genetic algorithm method is used to reduce the number of features, obtained through tree representation of ECG waveforms, for classification.

The roles of inference method and quantization algorithm in pattern classification of normal and abnormal ECG are studied.

A number of common abnormalities result in the ECG generators having amplitudes or sequences that are unusual and can be detected in the electrocardiogram through differences in signal morphology (contour). Based on the change in the morphology of ECG waveforms of two heart diseases, namely, myocardial infarction and left ventricular hypertrophy, Neural Network is used to classify the two diseases; Anteromyocardial Infarction and Left ventricular hypertrophy. The neural network is trained with both back propagation algorithm and as well as genetic algorithm.

1.5 OUTLINE OF THE THESIS

This introductory chapter, CHAPTER 1 has reviewed the literature on preprocessing, analysis and classification of ECG signals.

The following chapter, CHAPTER 2 deals with the problem and the need for the removal of powerline interference from ECG signals. Rule-based FIR and Wave digital filters with adaptive notch are developed, analyzed and compared with the performance of adaptive LMS filter.
CHAPTER 2 further deals with the development of a Genetic Algorithm based canceller for the removal of frequency-drifted sinusoidal wave powerline interference and frequency drifted sinusoidal wave interference with its third harmonic distortion. Finally the use of adaptive filter, cubic spline estimation and a combination of them in the removal of baseline wandering in ECG is reported.

On the whole, CHAPTER 2 deals with the preprocessing of ECG signals.

CHAPTER 3 elaborates the AI techniques developed for the analysis of ECG signals. Topics like extraction of nodes for data compression, extraction of skeletal features for classification, duration and amplitude measurements from tree representation and the generation of equivalent-tree using genetic algorithm are presented.

CHAPTER 4 reports on the classification of ECG based on AI techniques. Techniques like inference method, waveform matching method are used for identification of diseases. Back error propagation algorithm trained neural network and Genetic Algorithm trained neural network are dealt with for the identification and classification of two types of heart disorders.

CHAPTER 5 compares the performances of the techniques developed by this author with a number of techniques reported by other investigators for preprocessing, analysis and classification of ECG signals.

CHAPTER 6 concludes this thesis with an indication of the current trend in the handling of ECG signals, the related problems yet to be solved and hence the possible areas of study in the future.