1 Introduction

Chapter 1
Introduction

1.1 Biomedical signals

Biomedical signals like Electrocardiogram (ECG/EKG), Electroencephalogram (EEG), Electromyogram (EMG) are important from clinical point of view [1].

The electrocardiogram (ECG) is a graphic recording of the electrical potentials produced by cardiac tissue. The heart is unique among the muscles of the body in that it possesses the properties of automatic impulse formation and rhythmic contraction.

The ECG is recorded by applying electrodes to various locations on the body surface and connecting them to a recording apparatus. The connections of the apparatus are such that all upright deflection indicates positive potential and a downward deflection negative potential.

Bio potentials generated by rhythmic movement of heart are quasiperiodic. The features of the ECG are initially defined as P.Q.R.S.T and U. Now, with more complex analysis systems; the intrinsic features of the waveform can be further defined. Based on the past experience, treatment and other ECG independent tests, various conditions of the heart have been studied for the reflections in the electro-cardiogram. The physical shape and location, local nutrition, conduction, Harmon, Mental status, blood constitution and physical state affect the ECG greatly; various diseases also affect the ECG and drift it away from normal variants. Hence ECG is of diagnostic value in critical circumstances like Artial and ventricular hypertrophy, Myocardial ischemia and infarction, Pericarditis, Systemic diseases that affect the heart, Determination of the effect of cardiac drugs, especially digitalis and certain anti arrhythmic agents, Disturbances in electrolyte balance, especially potassium; and Evaluation of function of cardiac pacemakers.

The Electroencephalogram (EEG) is more than a test. It is an extension of the neurological examination and it gives the best results when combined with a good neurological history and examination. The EEG is the electronic documentation of the summated Excitatory and Inhibitory post-synaptic potentials generated in the brain.

There are various artifacts, which often contaminate electrocardiogram (ECG) signal. Some of them are power line interference, base line drift, random noise generated within the measuring instrument, cross talk, disturbances due to movement of recording electrodes, signal due to muscle-contraction: electromyogram (EMG) artifacts, etc. Because of this reason, signal to noise ratio (SNR) of ECG or other biomedical signals is very low.

Telemedicine is no longer just a playground for dreamers, enthusiasts and pilot programs. It has become a strategic tool for hard-eyed hospital administrators and entrepreneurial practitioners. In the last decade we have been witnessing a transformation-some call it a revolution-in the way we communicate, and the process is still under way. This transformation includes the ever-present, ever-growing Internet; the explosive development of mobile communications; and the ever-increasing importance of video communication. Data compression is one of the enabling technologies for each of these aspects of the multimedia revolution. It would not he practical to put images, let alone audio and video, on websites if it were not for data compression algorithms. Cellular phones would not be able to provide communication with increasing clarity were it not for compression. The advent of digital TV would not he possible without compression.

Essential tasks involved in signal processing are Filtering, Pediction, Compression, smoothing (averaging), encryption, Decryption, Reconstruction, Feature Extraction. Aim of this work is to develop various techniques to carry out signal processing for biosignals to improve efficiency with reference to applications such as telemedicine.

An Artificial Neural Network (ANN) is an attempt to mimic the action of the brain using simple structure. The ANN is built up using a class of adaptive machine that perform computation through process of learning. The large number of artificial neurons are interconnected to form the network. Thus neural network consists of a massively parallel distributed processors which has a neural propensity for storing experienced knowledge and making it available for use. ANN can be programmed or trained to store, recognize and associatively retrieve patterns or database entries; to solve combinational optimization problems, in summary, to estimate sampled functions when we do not know the form of the functions. The overall network behaves as an adaptive function estimator. This can be useful to carry out signal processing task like filtering, averaging, compression, detection etc.

The survey of literature for biomedical signal processing using traditional methods can be summarized as follows:

1.2 Filtering

There are many artifacts which contaminate the desired biomedical signal. Out of them, some artifacts arise from the subject. Examples of such artifacts are sweat artifact, EKG/ECG artifact, pacemaker artifact, Bi-metallic artifact, eye movement artifact, eye blink artifact, movement artifact, tremor, body rocking artifact, muscle artifact, pulse artifact, etc. Some of the artifacts arise from the recording equipment and environment also. They are 50/60 Hz interference, salt bridges, Amplifier blocking, Electrode popping, Electrodes of different metals, Supply line transients, static electricity, aliasing, photonic interference, telemetry etc. [2], [37].

A fundamental problem associated with signal processing is estimation of the shape of unknown waveform in a noisy signal. Electrocardiographic (ECG) signals are composed of a train of component wave (P, QRS and T waves) separated by iso-electric region [2]. ECG's recorded under exercise conditions are often corrupted by extraneous disturbances due to muscular activity (EMG noise) and respiration. The EMG noise is random in nature and has a frequency content existing over a wide range. Under exercise conditions, the level of these interfering signals, particularly the muscle noise component becomes large enough. Moreover, spectral content of muscle noise overlaps that of ECG. Hence, improvement of signal-to –noise ratio (SNR) solely by means of digital filtering is not possible. Basically there are two different approaches use to solve this problem: (1) Those which employ the structural features of the component wave and (2) Methods that use template matching techniques. Algorithm based on the first approach are of heuristic nature and are selective to the particular type of component wave being searched for (for example, the QRS complex) In the second approach, the approximate knowledge on the shape of the component wave is used to generate a template, which is determined by means of correlation, matched filtering, or other pattern recognition techniques.

Traditionally, a large number of algorithms for noise reduction in ECG's use either spatial or temporal averaging techniques [3]. Temporal averaging method requires a large number of beats or frames for effective noise reduction. Moreover, the averaging causes considerable errors particularly when the time alignment of beats is not accurately known, or especially when premature beats are present [4]. The main drawback of spatial averaging is the physical limitations to placement of a large number of electrodes at the same region.

Later on, several adaptive filtering methods have been proposed for detection and identification of the component waves from noisy ECGs, particularly adaptive

Gussian filter for detection of the QRS component from noisy ECG's [5]. Advantage of adaptive signal processing is that conventional operating systems operate in open-loop fashion while adaptive processors operate in a closed loop fashion [6]. Adaptive filtering of the EMG artifact was attempted with limited success. When the QRS complex disturbs the adaption process, re-adaption occurs and artifact appears [7]. Modification of algorithm was carried out in [8] but at the cost of reduction of sharp ECG amplitudes. Luo and Tompkins [9] could obtain better results with faster conversion using additional EMG channel. Rossi R. Casteli [10] proposed a low pass comb filter with reduced lobes in the frequency band above 50 Hz by cascading three averaging filters.

1.3 Compression

Need for ECG signal compression exists in many transmitting and storage applications. Transmitting the ECG signal through telephone lines, for example, may save a crucial time and unnecessary difficulties in emergency cases. Effective storage is required of large quantities of ECG information in the intensive coronary care unit, or in long-term (24-28 hours) wearable monitoring tasks (Holter) [11].

The compression of the signal is performed by removing redundancy. The redundancy exhibits itself in terms of statistical dependence between adjacent samples and the non uniformity of the amplitude probability of the quantized signals [12]. Linear correlation between neighboring samples may be removed, for example by various delta modulation methods or by linear prediction methods [13], while the non-uniform amplitude probability may be handled by entropy coding [13]. Biomedical signal compression methods can be divided into three functional groups:

1) Direct methods: where the samples of the signal are directly handled to provide the compression. Examples of the methods belonging to this group are: the turning point (TP) method,[14], the amplitude zone time epoch coding (AZTEC) method [15],[16], the coordinate reduction time encoding system (CORTES) [17], delta code algorithms, sample skipping [18], and SLOPE [19].

2) Transformation methods: where the original samples are subjected to a (Linear) transformation and the compression is performed in the new domain. Examples of methods belonging to this group are: Fourier transformation [20], Fourier descriptors [21], K-L transformation [22], and Walsh transform [23].

3) Parameter extraction method: where a preprocessor is employed to extract some features that are later used to reconstruct the signal. Examples of some methods belonging to this group are: peak picking [24], linear prediction methods [13], syntactic methods [25], and neural nets methods.

Several recent ECG data compression strategies have been proposed which exploit prior information on the locations in time of the heart bit subtraction with residual differencing, long term prediction with entropy coding, cycle pool based compression and vector quantization. Most of these methods utilize pseudo periodic behavior of ECG signals. Vector Quantization is extensively used in data compression systems [26]-[28]. Vector Quantization has proved to be an effective scheme for image data reduction [29] and is also very successful in coding speech parameters. Vector Quantization can also be employed in conjunction with any of the previous mentioned methods.

1.4 Detection

There are three distinct wave components in every cycle of an ECG viz. P, QRS complex and T (occasionally a Fourth Wave Component Viz U May Be Seen). For normal individuals each of these wave components has a specific wave shape corresponding to each lead, though slight but distinct variations can be noticeable. On the other hand, we can distinguish abnormal ECGs because of their difference in rhythm and/or morphologies. Thus by interpreting ECG, the manner of electrical conduction in the heart (normal or abnormal) can be understood. Hence for interpreting and ECG it becomes mandatory to detect the P, Q, R, S and T waves. Computer programs have been developed to aid in this task of ECG interpretation mainly because

(a) they can handle large volumes of data,
(b) they help to overcome human errors due to fatigue and bias,
(c) they also help to standardize the ECG interpretation and thus eliminate intra-observer variability.

A lot of work has been done for the computerized detection of QRS complexes. There have been both syntactic and non syntactic methods of delineation. The syntactic methods [30], [31] use templates for identification, these methods are very tedious and show no improvement in performance. Under the non syntactic methods are the following papers [30], [31], [32] Pan and Tompkins in their paper [30] developed a pre-processor scheme for QRS detection that is more or less considered a standard. However in the decision rule section, adaptive thresholding was used and for T wave detection, the slope criterion was used. This did not prove to be very reliable. Hence Hamilton and Tompkins in their paper [31] used the same pre-processor technique as in [30] but modified the decision rule section; they used a two-dimensional event vector with peak signal level and elapsed time from the last fiducial mark as parameters. They also used refractory blanking and search back methods to improve the detection efficiency. However this approach was found to be slow.

In [33], authors have describe a QRS complex detector based on the dyadic wavelet transform (D_y WT) which is robust to time-varying QRS complex morphology and to noise. We design a spline wavelet that is suitable for QRS detection. The scales of this wavelet are chosen based on the spectral characteristics of the electrocardiogram ECG signal. We illustrate the performance of the D_y WT based QRS detector by considering problematic ECG signals from the American Heart Association (AHA) data base. Seventy hours of data was considered. We also compare the performance of Dy WT based QRS detector with detectors based on Okada, Hamilton-Tompkins, and multiplication of the backward difference algorithms. From the comparison, results we observed that although no one algorithm exhibited superior performance in all situations, the D_y WT based detector compared well with the standard techniques. For multiform premature ventricular contractions, bigeminy, and couplets tapes, the D_y WT based detector exhibited excellent performance.

In [34] there is developed a real time algorithm for detection of the QRS complexes of ECG signals. It reliably recognizes QRS complexes based upon digital analyses of slope, amplitude, and width. A special digital band pass filter reduces false detection caused by the various types of interference present in ECG signals.

The thesis is organized in the form of ten chapters as follows:

Chapter: 1	The chapter provides an overview and the context for the remainder of the thesis.
Chapter: 2	Describes the sources of biomedical signals and need for the processing. The importance of the signals in the diagnosis is also described.
Chapter: 3	Gives the general preview of the conventional signal processing techniques is provided in this chapter with reference to biomedical signals.
Chapter: 4	It contains an overview of various ANN architectures and training algorithms used. It also describes the software tools available for development of ANN models and to carryout their simulation study.
Chapter: 5	It provides a comprehensive study of the work done by the

researchers using conventional techniques for the signal filtering. The ANN models for the signal filtering are developed and their performance is compared with conventional techniques.

Chapter: 6 It provides a comprehensive study of the work done by the researchers using conventional techniques for the signal compression. The ANN models for the signal compression are developed and their performance is compared with conventional techniques.

Chapter: 7 It provides a comprehensive study of the work done by the researchers using conventional techniques for the signal detection. The ANN models for the signal detection are developed and their performance is compared with conventional techniques.

Chapter: 8 It describes the design of GUI for the ANN based models developed and described in the chapters 5, 6 and 7.

Chapter: 9 It contains discussion of the results and proposes the direction for future work.

Chapter: 10 It contains Bibliography.