



EXTRACTION OF FIDUCIAL POINTS FROM ECG SIGNAL USING DWT

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cardiovascular diseases. A good performance of an automatic ECG analyzing system depends heavily upon the accurate and reliable detection of QRS complex, as well as P and T waves. ECG is generally recorded on a thermal paper which cannot be stored for a long time for analysis as the thermal trace gets erased gradually. To store the trace, the records are scanned and saved as images to maintain medical records. The memory occupied by this method is high and the regeneration of signal accuracy is less. This paper aims to propose an efficient method for extraction of fiducial points of ECG signals using DWT. Discrete wavelet transform is used for processing ECG recording, and extracting some features, and the Multi-Layer perceptron (MLP) neural network performs the classification task.

Keywords : Electrocardiogram, fiducial points, DWT, Multi-Layer Perceptron

INTRODUCTION

Cardiovascular disease is one of the widely spread lifestyle disease worldwide. ECG system has been adopted to monitor the heart's condition and measure process continuously. ECG is recorded on a regular basis on thermal paper. These ECG records are scanned and stored as images in hospitals for the assessment

of patients rehabilitation. The storage space required for these images is high and increases as the number of record per patient increases. Further, the retrieval time also increases, which plays a key role in Electronic Medical record (EMR) systems. Also the regeneration of scanned image accuracy is less. To overcome this problem, the ECG trace from the scanned images is extracted using improved method of DWT.

The ElectroCardioGram (ECG) signal is an important signal among all bioelectrical signals. Figure 1 illustrates two periods of the normal ECG signal. The P, Q, R, S and T waves are the most important characteristic

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features of the ECG. The peaked area in the ECG beat, commonly called QRS complex, together with its neighbouring P wave and T wave, is the portion of the signal through to

contain most of the diagnostically important information. Other important information includes the elevation of the ST segment and heartbeat rate, the RR or PP.

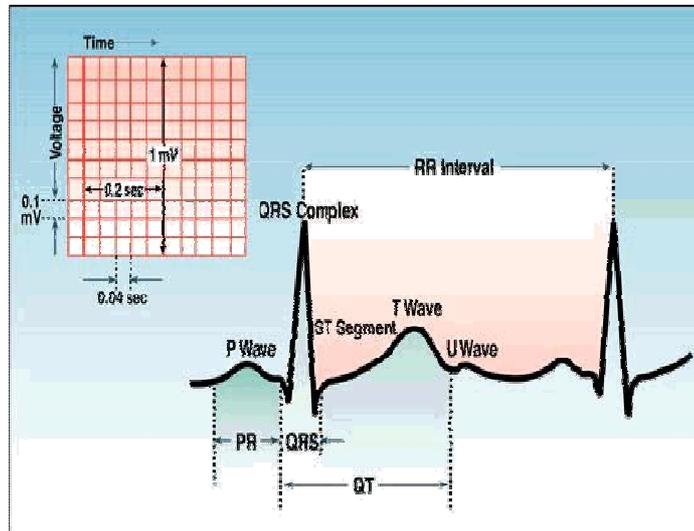


Figure 1. Two periods of the normal ECG signal [5].

The shape of ECG conveys very important hidden information in its structure. The amplitude and duration of each wave in ECG signals are often used for the manual analysis. Thus, the volume of the data being enormous and the manual analysis is tedious and very time-consuming task.

Naturally, the possibility of the analyst missing vital information is high. Therefore, medical diagnostics can be performed using computer based analysis and classification techniques. This paper aims to develop a simple, robust and improved technique that would derive digital time series ECG waveform from the scanned ECG image and extract the clinical information like amplitude and time interval of ECG parameters.

Materials and Methods

DISCRETE WAVELET TRANSFORM

The wavelet transform was presented at the beginning of the 1980s by Morlet, who used it to evaluate seismic data. Wavelets provide an alternative to classical Fourier algorithms for one and multi-dimensional data analysis and

synthesis, and have numerous applications such as in mathematics, physics, and digital image processing. The wavelet transform can be applied in both continuous time signal and discrete-time signal. This technique is based on the use of wavelets as the basis functions for representing other functions. These basis functions have a finite support in time and frequency domain. Multi resolution analysis is achieved by using the mother wavelet, and a family of wavelets generated by translations and dilations of it. In one dimensional DWT, at each decomposition level, the HPF associated with scaling function produces detail information which is related to high-frequency components, while the LPF associated with scaling function produces coarse approximations, which are related to low frequency components of the signal. The approximation part can be iteratively decomposed. This process for two-level decomposition is depicted in Figure 2. A signal is broken down into many lower resolution components. This operation is called the wavelet decomposition tree [24].

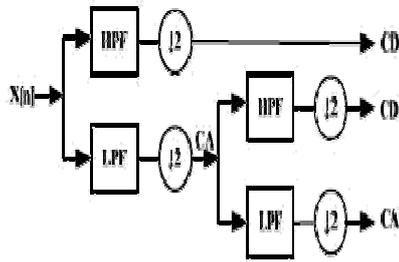


Figure 2. Sub-band decomposition of discrete wavelet transform implementation.

The wavelet transform is reversible. The reconstruction is the reverse process of decomposition. The approximation and detail wavelet coefficients at every level are up sampled by two, passed through the LPF and HPF and then added. This process is continued through the same number of levels as in the decomposition process to obtain the original signal. Figure 3 depicts this process.

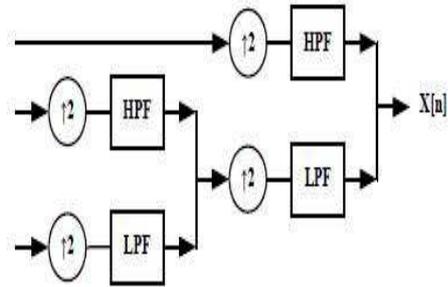


Figure 3. Wavelet reconstruction process.

Various wavelet families are defined in the literature. Daubechies wavelets are the most popular wavelets. The Daubechies wavelets are used in different applications. The wavelets filters are selected based on their ability to analyze the signal and their shape in an application. Figure 4 shows nine members of the Daubechies family.

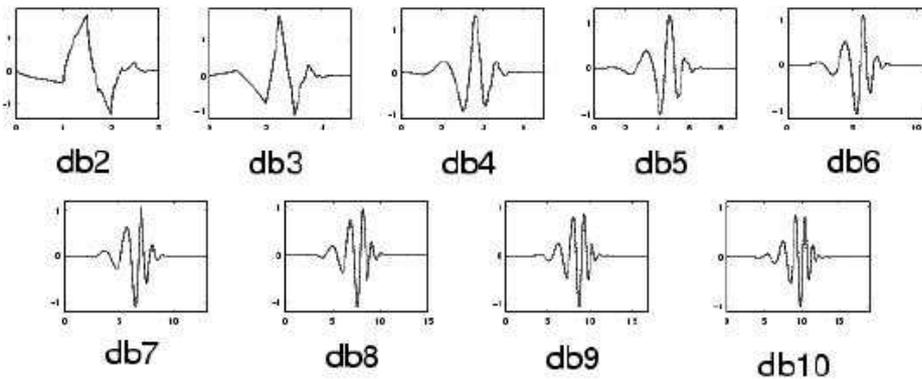


Figure 4. Nine members of the Daubechies family.

ARTIFICIAL NEURAL NETWORKS

The Artificial Neural Networks (ANN) are the tools, which can be used to model human cognition or neural biology using mathematical operations. An ANN is a processing element. It has certain performance characteristics in common with biological neural networks. A neural network is characterized by 1) its pattern of connections between the neurons (called its architecture), 2) its algorithm of determining the weights on the connections (called its training, or learning algorithm), and

3) its activation function [26]. The MultiLayer Perceptron (MLP) is the most common neural network. This type of neural network is known as a supervised network because it requires a desired output in order to learn. The purpose of the MLP is to develop a model that correctly maps the input data to the output using historical data so that the model can then be used to produce the output result when the desired output is unknown. A graphical representation of an MLP is shown in figure 5

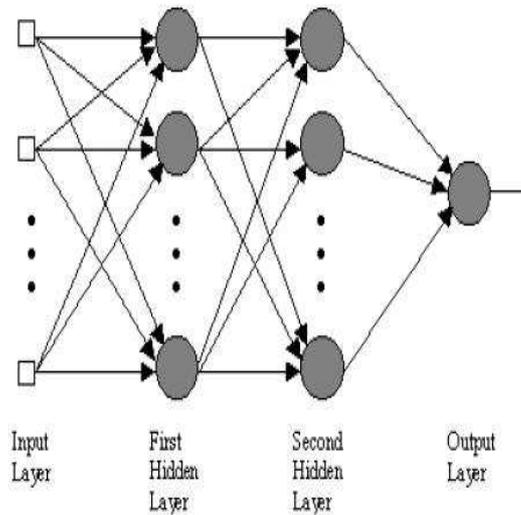


Figure 5. MLP architecture with two hidden layers [34].

In the first step, the MLP is used to learn the behaviour of the input data using back-propagation algorithm. This step is called the training phase. In the second step, the trained MLP is used to test using unknown input data. The back-propagation algorithm compares the result that is obtained in this step with the result that was expected. This kind of classification is called supervised classification. The MLP computes the error signal using the obtained output and desired output. The computed signal error is then fed back to the neural network and used to adjust the weights such that with each iteration the error decreases and the neural model gets closer and closer to produce the desired output.[5]

PROPOSED CLASSIFICATION SYSTEM

Figure 7 shows the block diagram of the proposed system. The system is based on wavelet transform and neural networks. The proposed system consists of two phases: the feature extraction phase and the classification phase. In the first phase, moving average filter is employed to eliminate the baseline noise from the ECG signals. Then the DWT is applied on filtered signal and some features from the wavelet coefficients are extracted. In the second phase, the extracted features are

used to train an MLP NN as the classifier.[5]

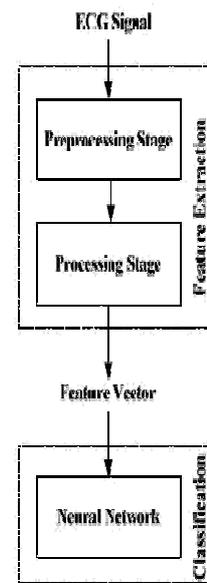


Figure 7. Block diagram of the proposed classification system.

FEATURE EXTRACTION PHASE

The first phase consists of two stages: preprocessing stage and processing stage. The preprocessing stage improves the classification accuracy of any algorithm; because, it gives us more accurate features. The obtained ECG from body electrodes has the baseline noise. Baseline wander, which may appear due to a number of factors arising from biological or

instrument sources such as electrode skin resistance, respiration, and amplifiers thermal drift. It is a low-frequency noise. In preprocessing stage, the ECG signal is filtered using the moving average filter to eliminate the baseline wander. Figure 8 depicts an original ECG signal along with its noise, which has the offset of 0.5. Figure 9 depicts the baseline eliminated ECG signal, which has the offset of 0.

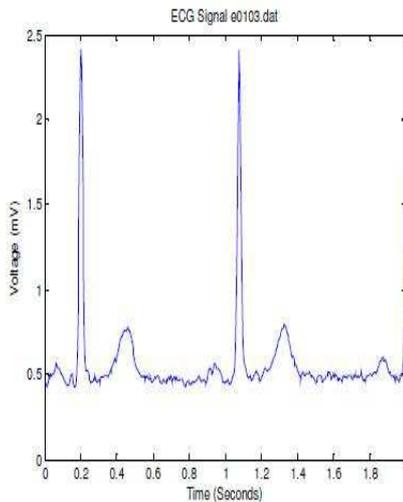


Figure 8. Original ECG signal with baseline noise which has the offset of 0.5.

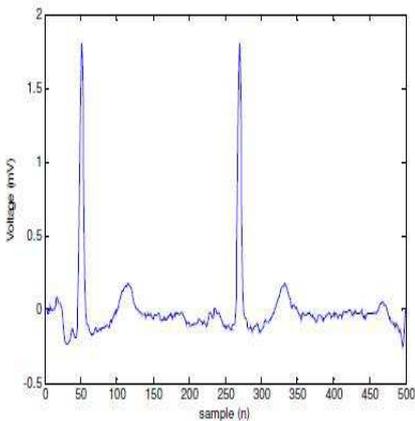


Figure 9. Baseline eliminated ECG signal which has the offset of 0

In the processing stage, the ECG features are extracted using selecting 2 Sec of an ECG records. For feature extraction stage, we used DWT. As already mentioned there are many

wavelet filters to apply on a signal. We have selected the Daubechies wavelet of order 6 (db6). This is because the Daubechies wavelet family is similar in shape to QRS complexes and their energy spectra are concentrated around low frequencies. The number of decomposition levels was set to 4. In other words, the ECG signals have been decomposed into the details D1-D4.

MORPHOLOGICAL FEATURE EXTRACTION

A. R-peak

One very peculiar feature that distinguishes the Fusion type from other types i.e. Normal and PVC types is the amplitude of the R-peak. Figure 3 depicts the R-peak distribution for the three classes. The R-peak is computed the difference between the mean level of the ECG sample and Rpeak. We observe that the three classes of heart beats are more or less distinctly separated.

B. QRS area Another important observation is that the QRS area for the three classes.

Results and Discussion

The ECG data is acquired from MITBIH arrhythmia database as it is considered as benchmark database. Each record is a continuous waveform. Hence it is necessary to extract only a single heartbeat. For this, first the R peak is detected and 90 samples on both sides of the peak are chosen. The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. In this paper, a neural network based system for automatic ECG arrhythmias classification was proposed.

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