Abstract

Detection and classification of electrocardiogram (ECG) signals are critically linked to the diagnosis abnormalities. Any abnormality in the wave shape and duration of the wave features of the ECG is considered as arrhythmia. This paper presents a diagnostic system for classification of cardiac arrhythmia from ECG data, using hybrid model of Artificial Neural Network and Fuzzy Logic. In an ECG, clinically useful information is obtained from the intervals and amplitudes of the cardiac waves. In an ECG, the non-stationary signal commonly changed its statistical property with time. In the proposed paper an algorithm based on wavelet packet tree classifier (for detection of QRS complex) has been implemented for the comparative study of automatic real-time ECG data. The amplitude and duration of the characteristic waves of the ECG can be more accurately obtained using Wavelet Packet Tree (WPT) analysis. WPT techniques have been employed to extract a set of linear (time and frequency domain) characteristics. Neuro-fuzzy techniques have been employed to extract a set of non-linear characteristic features from the transformed ECG signals. The real-time signals are obtained from various diagnostic centers. The hybrid model of Wavelet Packet Tree and Neuro-fuzzy network is proposed for the analysis and comparative study of an ECG signal.

Keywords:-Electrocardiogram (ECG), Wavelet Transform (WT), Neuro-Fuzzy model. Feature extraction

* Corresponding author. E-mail address: mahapatra.sakuntala@gmail.com
1. Introduction

The electrocardiogram (ECG) signal is a biomedical signal which is used in the diagnosis system to detect the abnormal electrical activity of the heart. ECG is a biomedical signal responsible for monitoring the state of the heart. It is also responsible for diagnosis of the abnormalities. It is a record of the wave passage that is generated by the heart muscles on repolarization and depolarization of the arteries and ventricles. The potential in the heart tissues is conducted to the body surface where it is measured using electrodes. The original data from the different time intervals such as PR, ST, QT intervals as shown in the figure (1). Here P wave shows the contraction interval of the arteries. QRS complex represent equivalent portion to the contraction of the ventricles and T wave is the relaxation of ventricles.

![Fig. 1. ECG signal](image)

The Electrocardiogram signal is widely utilized as the most important tool to study the heart state. The electrical activity of the human heart may be slower, faster or irregular than the normal signal results in case of cardiac arrhythmia. The ECG signals are non-stationary in nature, so the disorder of the heart may not appear at all times. For accurate diagnosis the ECG signal may be observed for disparate hours. This results in a high number of inputted data and the analysis turns out to be annoying and time consuming. Due to a long volume of data, the probability of an analyst to loss data is high. Hence there is a necessity in the diagnosis system to differentiate between the normal and abnormal signals. This helps the cardiologist for easy detection of the arrhythmia. Different intelligent systems have been developed for the analysis of the ECG signal. Here an algorithm has been used to detect the various classification problems. The main research related to ECG arrhythmias classification is the betterment of the performance of Neuro-fuzzy based classification by the application of Wavelet Transform (WT).

For the accurate analysis of an ECG signal, feature extraction is very important to detect the characteristics point and the different time intervals that can be used to detect possible cardiac abnormalities. Most of the times, the ECG signal is either corrupted or covered by noise. Wavelet analysis plays a very important role for the proper classification of the ECG signals as compared to other methods. Wavelet Transform (WT) has the property of Multi-scale Approximation Analysis (MSA) to provide both time and frequency domain information of the signal. The techniques of Wavelet Transform (WT) that have been used to observe the signal decomposition into a set of some primary functions are called wavelet. They are obtained from a single prototype wavelet by dilations, contraction and shift.

2. Proposed Model

Arrhythmia detection algorithm consists of following steps

(a) Preprocessing of the ECG signal
(b) Processing or features extraction
(c) Classification of the features of ECG Signal

Figure (2) shows the block diagram of the whole algorithm of the proposed model. The system is based on Wavelet Transform and Neuro-fuzzy network.
2.1 Preprocessing of the Signal

The received ECG signals from the body have acquired different noises. These noises may appear due to a number of factors arising from biological factors or instrumental sources. Skin resistance, respiration, motion artifacts, muscle contraction and expansion are the sources of noise related to the biological factors. Base line drift noises generated by electrodes, power line interference, and amplifier thermal drift dc offset are the sources of noise related to the instrumental factors. The ECG signals are manipulated due to these low frequency noises guided for the wrong diagnosis. Therefore, to reduce the noises, we have used the adaptive filter for ECG signal processing.

2.2. Processing or Feature Extraction Stage

ECG is the bioelectrical signal which is non-stationary in nature and Wavelet Transform (WT) is mainly used for the analysis of the non-stationary signals. The property of wavelet to calculate and manipulate data in compressed parameters is one of its very foremost application. These are called features. The Wavelet Transform can be applied to extract the wavelet coefficient from the discrete time signals. For the analysis of the non-stationary signal it is very much important to acquire correlation between time and frequency domain. Wavelet Transform (WT) provides the time and frequency domain analysis of the signal. In Wavelet Transform fixation of a signal is in the time domain via translation the mother wavelet, and in the frequency domain it is via expansion of the mother wavelet. Expansion or dilation function of the discrete wavelet transform can be represented as a tree of filters like low pass and high pass as shown in figure (3). The original signal is decomposed into components of lower frequency are only considered, high frequency components are not analyzed. The maximum number of decomposition that can be performed in a data with 2N samples using DWT is N discrete levels\(^2\).

Thus the ECG signal consisting of many data points can be compressed into a few parameters which can reflect the behavior of the signal. This feature using the smaller number of parameters to represent the ECG signal can be used for classification purpose. In the present model we are employing sub-band analysis of the wavelet co-efficient. Sub-band analysis is the method which is a form of converting the coding that breaks the received signal in to number of different frequency bands and analyze each one independently. In this model, ECG signals are decomposed into 4 levels using Wavelet Transform. Each cycle in each type of ECG signal consists of 264 data points. Then approximate and detail coefficients are calculated based on 4 levels of decompositions of each beat shown in the figure (3). For wavelet analysis the input sequence x (n) is passed through several levels of low pass filter g(n) and high pass filter h(n). At each level, detail information is produced by the high pass filter where as the approximate information is produced by the low pass filter. The figure (3) shows two level decomposition, but in our application four level decomposition is used.

![Diagram](image)

Fig.2. Proposed Model

![Diagram](image)

Fig.3. Wavelet Tree

From the obtained approximation the detailed co-efficient, Sub-band Energy (SE) is calculated. SE is given as
Where $C$ is the co-efficient, $n$ represents the sub-band and $N$ is the total no of co-efficient in the sub-band. The following statistical parameters are calculated:

- Normalized Sub-band Energy (NSE)
- Mean Sub-band Energy (MSE)
- Relative Mean Sideband Energy (RMSE)

NSE is mathematically calculated as the sub-band energy divided by the total number of coefficients in the sub band. MSE is defined as the sub-band energy divided by the total no of co-efficient in the sub-band. RMSE is defined as the mean sub-band energy divided by mean total energy. The three parameters: NSE, MSE, RMSE are considered as Feature Set (FS). The FS are fed to the Neuro-fuzzy network for classification purpose.

2.4 Classification of Signal

In the field of artificial intelligence system, neuro-fuzzy network is the hybrid network, which formed by combination of artificial neural networks and fuzzy logic. Neuro-Fuzzy network was proposed by J. S. R. Jang. Neuro-fuzzy hybridization results in a hybrid intelligent system that analyses these two techniques by combining the human-like intelligent techniques of fuzzy systems with the learning and joining structure of neural networks. Neuro-fuzzy network performs the human like reasoning style of fuzzy systems. The use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The main strength of neuro-fuzzy systems is that they are universal approximators with the ability to implore explainable IF-THEN rules. The Neuro-fuzzy system has been considered in this paper is described in figure (4).

The change affects only the equations of the fourth layer, while the structure diagram is similar. Its construction is based on fuzzy rules of the form:

\[
\text{Rule:} \quad \text{If } x_1 \text{ is } A_{1j} \text{ and } x_2 \text{ is } A_{2j} \ldots \text{and } x_m \text{ is } A_{mj} \text{ then } y_1 \text{ is } \beta_{1j} \ldots y_M \text{ is } \beta_{Mj}
\]  

(1)

Where $m$ is the dimension of the input vectors (number of preserve features), and $j$ is the rule index ($j=1\ldots K$). The number of output neurons of the last layer corresponds to the number of classes and it is equal to $M$. Neuro-fuzzy system keeps the advantages of the original fuzzy network described by Chen & Teng for identification in control system. Its structure allows us to construct the fuzzy system rule. In the network each neuron performs two actions using two different functions.

**Fig.4.** Structure of Neuro-fuzzy System

(a) The accumulation function $g^k()$, which computes the net input.

\[
\text{Net input} = g^k(x^k, W^k)
\]  

(2)

Where the superscript indicates the layer number ($k=1\ldots 4$), $x^k$ is the input vector and $W^k$ is the weight vector.
(b) $f^k()$, is the non-linear function which gives the output.
Output $= O^k_i = f^k(g^k)$

Where $O^k_i$ is the i-th output of the k-th layer.

Layer 1 is the fuzzifying inputs,

$$O_{1,i} = \mu A_i(x), \text{ for } i=1, 2 \text{ and}$$

$$O_{1,i} = \mu B_i(y), \text{ for } i=3, 4,$$

Where O is the output of the layer 1, node i

Layer 2 calculates the firing strength of a rule,

$$O_{2,i} = w_i = \mu A_i(x) \mu B_i(y), \text{ for } i=1, 2.$$ (6)

Layer 3 normalize firing strength of the node 1,

$$O_{3,i} = \frac{w_i}{W_1^i + W_2^i}, \text{ for } i=1, 2.$$ (7)

Layer 4 calculates the conclusions,

$$O_{4,i} = A_i = \frac{w}{W} f_i = \frac{w}{W} (p, x+q, y+r_i).$$ (8)

3. Results and Analysis

For our proposed work we have used the real time signals for the analysis and minimization the errors. We are using discrete wavelet transform for the feature extraction of the signal by the four level wavelet decomposition. Then finally the decomposed Feature Set (FS) are employed across the Neuro-fuzzy system for the classification of the ECG signal. Figure (5) is the original signal, figure (6) is the decomposed signal, figure (7) shows the comparison curve between desired and actual output.

Fig.5. Original ECG signal

Fig.6. Wavelet decomposed signal
4. Conclusion

This paper represents an ideal approach for the ECG signal analysis. The analysis and classification of the ECG Signal is done using the Artificial Neural Network (ANN) and Neuro-fuzzy network. As shown in figure (8) (comparison of training curves between ANN and Neuro-fuzzy network), hybrid network provides a better error minimization as compared to the neural network. Due to short processing time and higher accuracy of the proposed method, Neuro-fuzzy network can be used as a real-time arrhythmia classification system. Higher accuracy of the system makes it highly reliable and efficient.

References