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Multi Resolution Analysis of ECG for Arrhythmia Using Soft-Computing Techniques

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Abstract
in this paper, ECG signal analysis for arrhythmia detection using discrete wavelet transform and Back Propagation Neural Network is addressed . Several algorithms have been proposed to classify ECG arrhythmias; however, they cannot perform very well. Therefore, in this paper, an expert system for Electro Cardio Gram (ECG) arrhythmia classification is proposed. Proposed technique used to detect the abnormal ECG Sample and classify it into two different classes (normal and **Arrhythmia**). We have employed MIT-BIH arrhythmia & Normal Sinus Rhythm (NSR) database and chosen 62 files of ten second recording where 14 files are considered as normal class and 48 files of **Arrhythmia** class out of total 62 files. The features are break up in to two classes that are DWT based features and morphological feature of ECG signal which is an input to the classifier. Back Propagation Neural Network (BPNN) are employed to classify the ECG signal and the stem performance is measured on the basis of percentage accuracy. For the normal class sample 100% of accuracy is reached whereas 97.9% accuracy is achieved for **Arrhythmia** class sample. The overall system accuracy obtained is 98.4 % using (BPNN) classifier.
Keywords: ECG, Arrhythmia, , Discrete Wavelet Transform (DWT), BPNN, Accuracy

I. INTRODUCTION

The electrical activity of the heart showing the regular contraction and relaxation of heart muscle signifies as Electrocardiogram (ECG). The analysis of ECG waveform is used for diagnosing the various heart abnormalities. The heart conditions is used to diagnose by an important tool called Electrocardiography. ECG signal processing techniques consists of, de-noising, baseline correction, parameter extraction and arrhythmia detection. An ECG waveforms consists of five basic waves P, Q, R, S, and T waves and sometimes U waves. which is shown in figure 1. The P wave represents atrial depolarization, Q, R and S wave is commonly known as QRS complex which represents the ventricular depolarization and T wave represents the repoalrization of ventricle [1]. The most important part of the ECG signal analysis is the shape of QRS complex. The ECG signal may differ for the same person such that they are different from each other and at the same time similar for different types of heartbeats [2]. 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 [3]. The pacemaker cells inside the sinoatrial (SA) node used to generate and regulate the rhythm of the heart, which is located at the top of the right atrium. Normal heart beat is very regular, and atrial depolarization is always followed by ventricular depolarization. In the case of arrhythmia this rhythm becomes irregular, that is either too slow or too fast. Several algorithms have been proposed to classify ECG heartbeat patterns based on the features extracted from the ECG signals to increase the accuracy and sensitivity. Fourier transform analysis provides the signal spectrum or range of frequency amplitudes within the signal; however, Fourier transform only provides the spectral components, not their temporal relationships. Wavelets can provide a time versus frequency representation of the signal and work well on non-stationary data [4-6]. Other algorithms use morphological features [7], heartbeat temporal intervals [8], frequency domain features and multifractal analysis [9]. Autoregressive Modeling [10], RBF Neural Networks [11], selforganizing map [12], and fuzzy c-means clustering techniques [13].

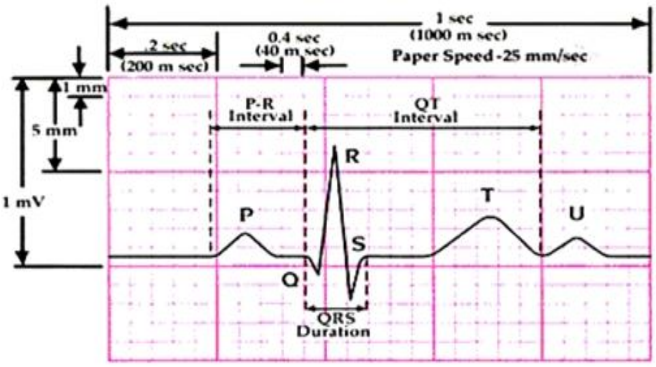

Figure 1 Normal ECG Waveform

II. METHODOLOGY

The block diagram of employed method is shown in figure 2. From the figure the whole methodology is divided into three basic parts: Preprocessing, feature extraction and classification. it can be seen that the raw ECG signal is offered for preprocessing.

The original ECG signal should be pre-processed with the purpose of removing existed noises of ECG and preparing this processed signal for the next stage. The preprocessing stage further divided into de-noising and Baseline wander removal of ECG signal. The next stage of the proposed model is feature extraction that is preparing the input which best characterize the original signal. Final step of the method is to classify the processed signal into the normal and arrhythmia class.

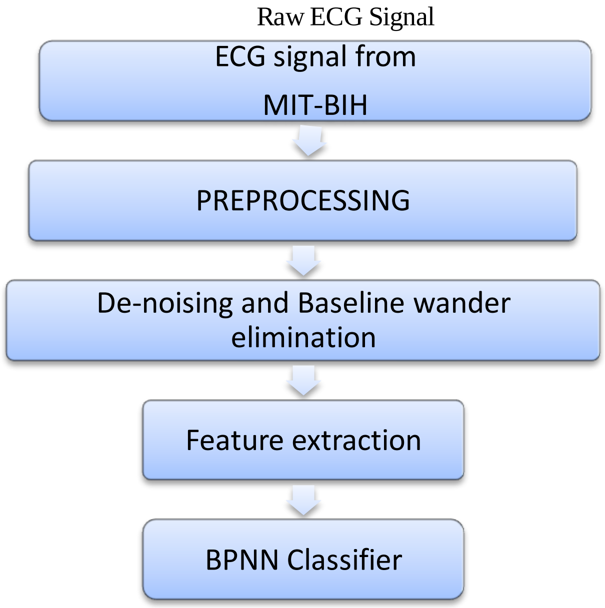

Figure 2 Block diagram of Arrhythmia detection method of ECG signal

III. DATABASE COLLECTION

For this Paper, MIT-BIH Arrhythmia Database directory of ECG signals from physionet is utilized. The resources of the ECG signal of MIT-BIH Arrhythmia & Normal Sinus Rhythm (NSR) Database were obtained by the Beth Israel Hospital Arrhythmia Laboratory. This database contains 14 file for Normal Sinus Rhythm (NSR) and 48 files for Arrhythmia of 30 minutes recording divided into two parts first one is of 23 files (numbered from 100 to 124 with some numbers missing), and another one contains 25 files (numbered from 200 to 234, again with some numbers are absent). [14]-[15].

This database comprises approximately 109,000 beat labels. The ECG waveforms from MIT-BIH Database are exemplified by- a text header file, a binary file and a binary annotation file. The header files explain the detailed information such as number of samples, sampling frequency, format of ECG signal, type of ECG leads and number of ECG leads, patients history and the detailed clinical information. The ECG signals are stored in 212 format , in binary annotation file, which means each one sample imposes number of leads times 12 bits to be stored and the binary annotation file consists of beat annotations [15].

IV. PREPROCESSING

The first stage of ECG signal processing is preprocessing, where it is necessary to eliminate noises from input signals using Wavelet Transform. For pre-processing of the ECG signal, noise elimination involves different strategies for various noise sources [16]. This pre- process of ECG signal is done before the extracting the feature, can result better extracted features to increase the system efficiency. Preprocessing of ECG signal consists of De-noising of ECG signal and baseline wander removal using multi-resolution wavelet transform.

A. De-noising In this stage the different noise structures are eliminated using daubechies wavelet of order four. De-noising Procedure of the Signal consists of three important steps [16].The signal details are influenced by high frequencies at the first level, whereas the low frequencies influence the approximations of one dimension discrete signals. Wavelet Transform method for de-noising of the ECG signal decomposes the signal into different components that materialize at different scales. In the first step, the appropriate wavelet function is selected and decomposed the signal at level N. next step is to select the Threshold using various techniques, in this paper the automatic thresholding techniques is employed. After selecting a threshold (soft threshold) apply it for each level to the detail coefficients. In the last stage, signal is reconstructed based on the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N [17]. Figure 3 & 4, visualize the Original ECG signal, and Baseline wander Removed ECG signal.

B. Baseline wanders removal

The noise artifacts that generally affect ECG signals is Baseline wandering. Normally it appears from respiration and lies between 0.15 and 0.3 Hz. Elimination of baseline wander is therefore needed in the ECG signal analysis to diminish the irregularities in beat morphology. In this paper, the baseline wander of ECG waveform is eliminated by first loading the original signal then smooth's the data in the column vector y using a moving average filter. Results are obtained in the column vector y[17]. We have selected span for our work for smoothing the data is 100 for smoothing it and finally subtracted the smoothed signal from the original signal. Hence, this computed signal is free from baseline drift.

V. FEATURE EXTRACTION

After the noise elimination, baseline wanders removal and peak detection it is necessary to extract the feature of the ECG waveform in order to use it in the next stage of ECG signal analysis. The ability to manipulate and compute the data in compressed parameters form is one of the most important application of wavelet transform, are often known as features. Feature extraction is the most important step in pattern recognition. There are several ways to extract the feature of ECG signal. In this work, there are two types of features are extracted of ECG waveforms.

i. Morphological feature of ECG signal
ii. Wavelet co-efficient based features

Selection of appropriate Feature plays an important role in pattern recognition. The computed DWT coefficients present a compact representation that demonstrates the energy distribution of the signal in time and frequency [18]. In this stage by using daubechies wavelet of order four with level five extracted the statically feature Hence, the calculated approximation and detail wavelet coefficients of the ECG signals were applied as the feature vectors representing the signals. Direct using of wavelet coefficient as inputs to the neural network may increase the neuron numbers in hidden layer which in turn has a harmful impact on network operation. In order to minimize the dimensionality of the extracted feature vectors, the statistics of the wavelet coefficients were utilized.[1] The following statistical features were utilized to represent the time-frequency distribution of the ECG waveforms:

1. Mean of the absolute values of the details and approximation coefficients at each level.
2. Standard deviation of the details and approximation coefficients in each level.
3. Variance values of the details and approximation coefficients at each level.
4. Power Spectral Density of ECG Signal
5. Energy of Periodogram of ECG Signal

Finally for each of ECG signals 20 wavelet based feature have been obtained. Apart from statistical feature, the morphological feature of ECG signal is also obtained. These feature , maximum values of P, Q, R, S, T peaks. Therefore the total 25 feature have been obtained to apply as an input to the neural network. Since the quantities of the feature vector may be quite different, a normalization process is required to standardize all the features to the same level. Normalizing the standard deviation and mean of data permits the network to treat each input as equally essential over its range of values.

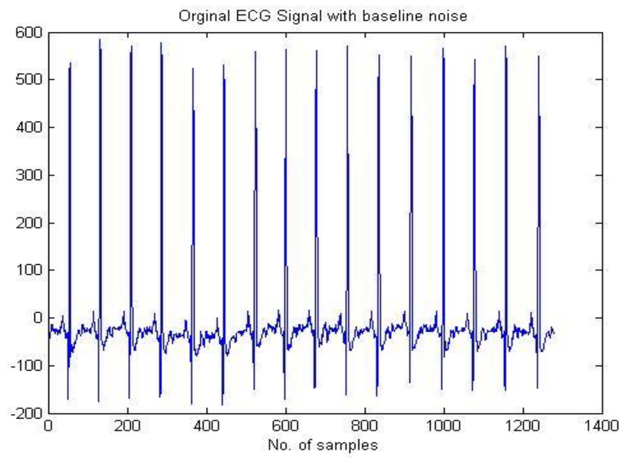

Figure 3 Original ECG signal with baseline noise which has the some offset

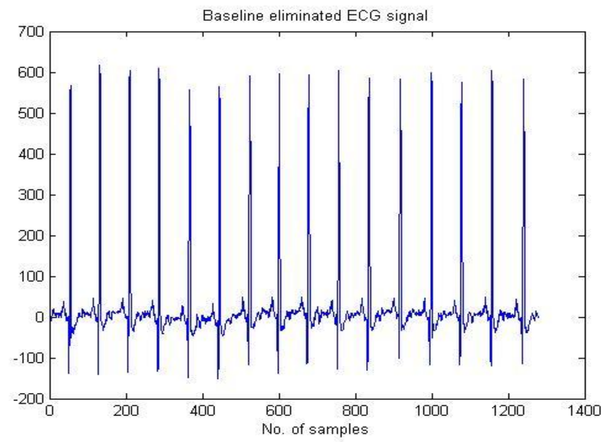

Figure 4 baseline eliminated ECG signal which has the offset of 0

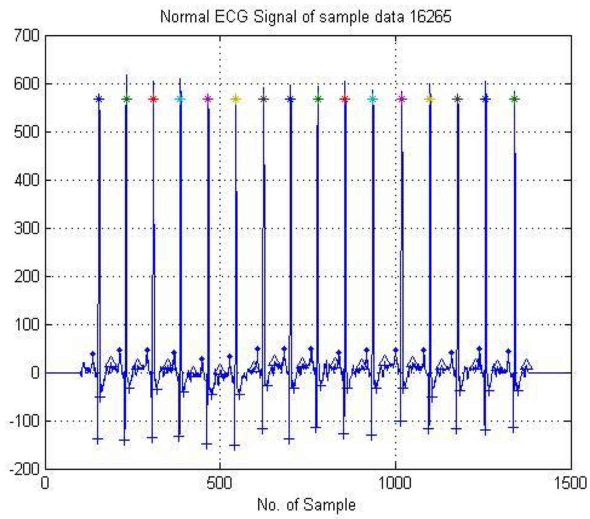

Figure 5 Normal ECG signal of sample data 16265

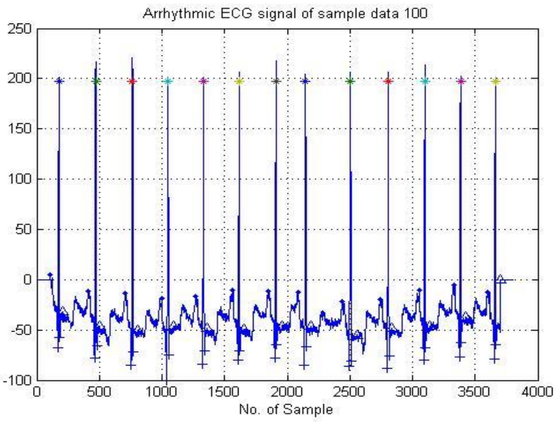

Figure 6 Arrhythmic ECG signal of sample data 100

VI. NEURAL NETWORK CLASSIFIER

Artificial neural network (ANN) is generally called neural network is a computational model which is motivated by the structure of biological neural networks. A neural network consists of an interconnected group of artificial neurons. This paper describes the use of neural network in pattern recognition , where the input units represents the feature vector and the output units represents the pattern class which has to be classify. Each input vector (feature vector) is given to the input layer, and output of each unit is corresponding element in the vector. Each hidden units calculates the weighted sum of its input to outline its scalar a net activation. Net activation is the inner product of the inputs and weight vector at the hidden unit [19].

A. Back Propagation Neural Network

The back-propagation neural network (BPNN) allows practical acquirement of input/output mapping information within multilayer networks. BPNN executes the gradient descent search to minimize the mean square error (MSE) between the desired output and the actual output of the network by adjusting the weights. Back propagation algorithm is highly precise for most classification problems for the reason that the characteristics of the generalized data rule [20-21].

VII. SIMULATION RESULTS AND DISCUSSUOIN

The MIT-BIH arrhythmia & NSR database is divided into two separate classes that are normal and arrhythmia. The Each file of ten second recording was picked up data and it is separated into two class based on the maximum number beats type present on it. Among 67 ECG recording each of length 30 minutes, only 62 recordings (14 records of normal class and 48 from arrhythmia class) of length ten second are considered for this work and the record number 19088,19090,19093,19140 and 19830 are not considered in this study. The table 1 shows the utilized records number from MIT-BIH NSR & arrhythmia database. The total 25 number of features are splited in to two separate classes. These are DWT based features and morphological feature of ECG signal. Since, there are 25 (20 DWT based feature and 5 morphological) features are extracted which is given as an input to the BPNN classifier. To simulate and train the network, 62 data (14 from normal class and 48 from abnormal class) are utilized. Combining the extracted features, the 70% of this data (64 × 25) matrix has been achieved for training input data and 15% of extracted feature(64×25) are used for validation and remaining 15% of extracting feature matrix data(64×25) are used for testing the network.

Table 1 Distribution of records of MIT-BIH NSE & arrhythmia database

Class	Records Number
Normal Class	16265-16272-16273-16420-16430-16483-16539-16773-16786-16795-17052-17453-18177-18184-19088-19090-19093-19140-19830
Arrhythmia Class	100-101-102-103-104-105-106-107-108-109-111-112-113-114-115-116-117-118-119-121-122-123-124-200-201-202-203- 205-207-208-209-210-212-213-214-215-217-219-220-221-222-223-228-230-231-232-233-234

The simulation result has been obtained by using back propagation neural network (BPNN) classifier and the 10 numbers of neurons in the hidden layer is used for training and testing the ECG signal. Two neurons are used at the output layer of the network as (1,0) and (0,1) referring to normal and Arrhythmia class.

The most crucial metric for determining overall system performance is usually accuracy. We defined the overall accuracy of the classifier for each file as follows:

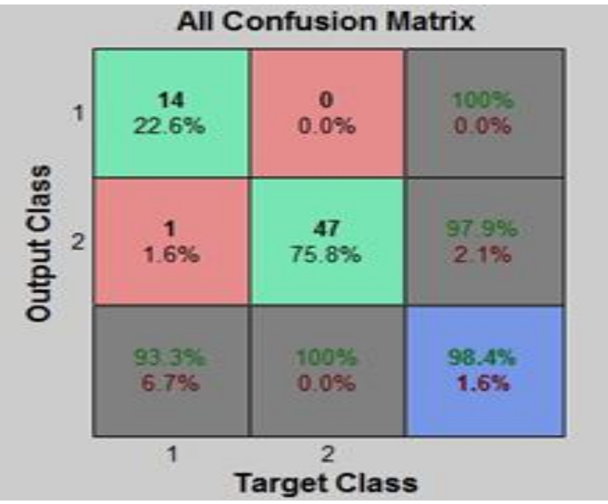

Figure 7 Confusion Matrix of BPNN Classifier

From figure 7, the Simulation result is shown in terms of confusion matrix of the neural network. The confusion matrix illustrating the classification results of the back propagation neural network (BPNN) is shown in Table 2. According to the confusion matrix, 1 normal sample is classified correctly by BPNN as a normal sample, that means 14 normal sample are classified correctly out of 14 sample whereas there is no misclassification carried out for normal ECG sample. But for arrhythmia sample, arrhythmia sample is classified wrongly by BPNN as a normal sample, that means 47 arrhythmia sample are classified correctly out of 48 sample whereas there is misclassification carried out for arrhythmia ECG sample The classification accuracy is 100% for normal sample detection and 97.9% for arrhythmia class data. The overall system performance was achieved with 98.4 % accuracy.

Table 2 The overall performance of BPNN are shown

Type of Sample	No. of Sample	Detection by NN	Accuracy
Normal	14	14	100%
Arrhythmia	48	47	97.9%
Total	64	63	98.4%

VIII. CONCLUSION

This work reveals that the abnormality detection of the ECG signal based on discrete wavelet transform and BPNN is 100% efficient. We have classified the MIT-BIH NSE & arrhythmia database records into normal and arrhythmia classes based on the types of ECG beats present in it. Out of 68 records, the 62 records of ten second recording are considered for classify the ECG signal whereas the remaining 5 records are excluded for this study. Since, total 62 records and 25 features are used in this study to classify the signal. We have achieved overall accuracy of 98.4% using back propagation neural network (BPNN) with 10 numbers of neurons in the hidden layer. The result for training and testing the normal and arrhythmia data sample is greater than 90% using BPNN classifier which shows the improved efficiency of the proposed work.

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