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ECG Analysis Using Wavelet Transform and Neural Network

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Abstract:–In this work, we have developed an algorithm to detect and classify three types of electrocardiogram (ECG) signal beats including normal beats (N), right bundle branch block beats (R), left bundle branch block beats (L)using a neural network classifier. In order to prepare an appropriate input vector for the neural classifier several pre-processing stages have been applied. Discrete wavelet transform (DWT) has been applied in order to extract features from the ECG signal. Finally, the MIT-BIH database is used to evaluate the proposed algorithm, the overall classification accuracy rate is more than 99%..

Keywords:–Electrocardiogram (ECG), Wavelet Transform, Artificial Neural Network (ANN)

I. INTRODUCTION

The ECG is a diagnosis tool that reported the electrical activity of heart recorded by skin electrode. It is a noninvasive technique that means this signal is measured on the surface of human body, which is used in identification of the heart diseases. Any disorder of heart rate or rhythm, or change in the morphological pattern, is an indication of cardiac arrhythmia, which could be detected by analysis of the recorded ECG waveform. The ECG as shown in Fig.1 records the electrical activity of the heart, where each heart beat is displayed as a series of electrical waves characterized by peaks and valleys. Normally, the frequency range of an ECG signal is of 0.05–100 Hz and its dynamic range of 1–10 mV [12].One cardiac cycle in an ECG signal consists of the P-QRS-T waves. Most of the clinically useful information in the ECG is found in the intervals and amplitudes defined by its features [4] .The aim of this work is to develop effective algorithms to solve problems associated with arrhythmia recognition. In order to achieve following aspects of ECG analysis are discussed.

i) Wavelet transform is a very promising technique for time frequency analysis. By decomposing signal into elementary building blocks that are well localized both in time and frequency, the WT can characterize the local regularity of signals[1][2]. This feature can be used to distinguish ECG waves from serious noise, artifacts and baseline drift. Therefore wavelets are used to extract the significant information from the ECG signal.
ii) A supervised artificial neural network is developed to recognize and classify the nonlinear morphologies. Supervised learning requires standard data while training; hence ECG recordings from MIT-BIH (Massachusetts Institute of Technology-Beth Israel Hospital Arrhythmia Laboratory) arrhythmia database with a sampling frequency of 360Hz are employed in this work

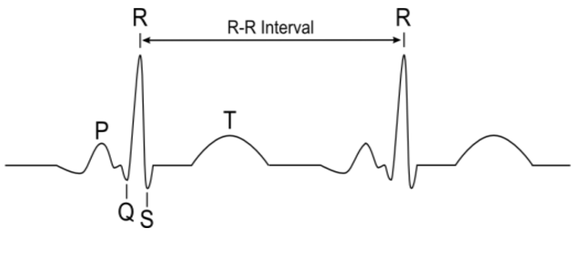
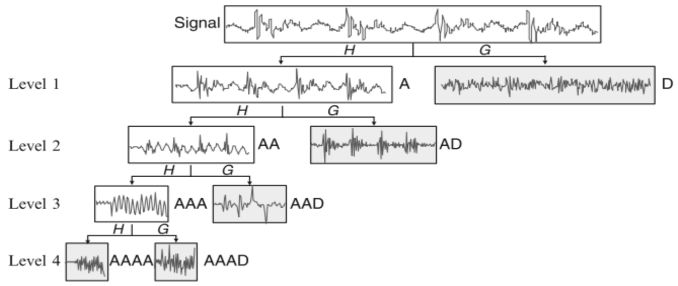


Fig.1: ECG Wavefom

II. MATERIALS

2.1 Wavelet transform

The wavelet transform (WT) is a powerful tool of signal processing for its multiresolutional possibilities. Unlike the Fourier transform, the WT is suitable for application to non-stationary signal, whose frequency response varies in time [9]. In Practice, the Discrete Wavelet Transform (DWT) is computed by passing a signal successively through a high pass and a low pass filter. For each decomposition level, signal x convolve with low pass filter for approximation coefficient (A), and with high pass filter for detail coefficient (D). The signals would be continuously seperated into low frequencies and high frequencies as shown in Fig.2



Note: H - Low pass filter; G - High pass filter; A - Approximate information; D - Detailed information

Fig. 2: DWT Process [3]

2.2 Selection of Wavelet base

There are number of wavelet families like haar, coiflet, Biorthogonal, Daubechies (Db), Symlet, etc. for analysis and synthesis of signal. There is no absolute way to choose a certain wavelet. The choice of the wavelet function depends on the application. The haar wavelet wavelet algorithm has the advantage of being simple to compute and easy to understand. The symlet algorithm is conceptually more complex and has a slightly higher computational overhead. But, the symlet algorithm picks up detail that is missed by the haar wavelet algorithm. The Proper selection of wavelet basis function is important in analysis. Since symlet is mostly morphologically similar to the ECG signal, so in present work symlet is used in analysis. It has the maximum cross correlation coefficient between the ECG signal and the chosen base wavelets. Sym7 wavelets have better detection for ECG (Abi-Abdallah et al.2006).

In short, the mother wavelet should have compact support, and the basis functions should be orthonormal. Compact support makes the wavelet transform able to work on finite signals to discriminate signal features in both time and scale, while orthogonality is needed so as to maximally decorrelate the data in a signal [3]. sym7 wavelet from Symlets family which is compactly supported with least asymmetry than ‘coif5’ which is symmetric wavelet but requires large support width. The number of decomposition levels is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlate well with the frequencies required for classification of the signal are retained in the wavelet coefficients. In the present study, the numbers of decomposition levels are chosen to be 4 since most of the energy of the ECG signal lies between 0.5 Hz and 40 Hz[12].

III. METHODS

The aim of the work is to recognize and classify the normal beat and different types of arrhythmias present in the ECG record. The following steps are implemented by the proposed method

1. ECG signal Preprocessing for removing noise, power-line interference, baseline wandering.
2. Feature extraction and Feature selection by wavelet
3. To design and train the neural network for arrhythmia recognition in supervised manner. Designing of Neural Network by back-propagation algorithm for classification
4. To test the neural network for classification of beats into distinct classes Normal beats (NB), Left Bundle Branch Block (LBBB), and Right Bundle Branch Block (RBBB)

3.1 Preprocessing of Signal

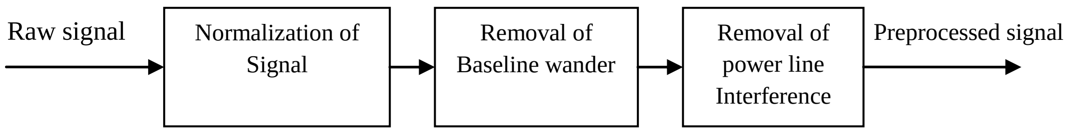


Fig.3: Preprocessing of Signal

The power line interference and the baseline wandering are the most significant and can strongly affect ECG signal analysis. Filters are used to alter or remove unwanted components from signals. Digital filters can be classified into Finite Impulse Response (FIR) filters and Infinite Impulse Response (IIR) filter.

The impulse response of FIR filter to input is 'finite' because it settles to zero in a finite number of sample intervals. This is in contrast to IIR filters which have internal feedback and may continue to respond indefinitely IIR filters are chosen as they provide high throughput and sharp cutoff frequencies[14]. The Butterworth digital IIR filters are used for noise removal as they are characterized by a magnitude response that is maximally flat in the pass-band and monotonic overall.

[b, a] = butter (N, Wn, 'ftype')

The above MATLAB IIR function designs a high-pass, low-pass, or band-stop filter with normalized cutoff frequency Wn. N is the order of filter which presents the number of stages used in the design of analog filter

1) Normalization of ECG samples: Each sample is preprocessed by firstly removing the mean value to eliminate the offset effect, and then dividing with the standard deviation. This process results in normalized signals with zero mean and unity standard deviation, which aims to reduce the possible false decisions due to signal amplitude biases resulting from instrumental and human differences.
2) Removal of Noise from signal
   a) The power line interference was eliminated using band stop butter filter with 49.2Hz- 50.8 Hz cutoff frequency.
   b) The frequency content of the base line wander is usually in a range well below 0.5Hz .so high pass butter filter is employed with cutoff frequency 0.8 Hz to remove noise due to the respiration

3.2 DWT approach

In the arrhythmia database used , The sampling frequency of the records is 360 Hz. The number of decomposition levels is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that Correlate well with the frequencies required for classification of the signal are retained in the wavelet coefficients. In this work, the numbers of decomposition levels are chosen to be 4. MATLAB’s wavelet toolbox provides various different wavelet functions for signal decomposition. A WAVEDEC function is used to perform a multilevel 1-D wavelet analysis using a specific wavelet type.

[C, L] = WAVEDEC(X, 4, 'wtype') (refer [10])

Returns the wavelet decomposition of the signal X at level 4, using 'sym7'

In arrhythmias RR interval is one of the important features. In some arrhythmias RR interval (time interval between the processing R peak to neighboring R peak) varies with normal arrhythmia beat. In premature beats RR interval between the processing beat and the previous beat (RR_1) is shorter than normal, and the RR interval between the processing beat and next beat (RR_2) is longer than normal . Most of the energy of the ECG signal lies between 0.5 Hz and 40 Hz. This energy of the decomposition coefficients is concentrated in the lower sub-bands A_4; D_4; D_3 . The detail information of levels 1 and 2 (sub-bands D_1; D_2) are discarded, as the frequencies covered by these levels were higher than frequency content of the ECG. Totally 23 DWT coefficients are selected from A4; D_4; D_3 sub-bands. Along with the selected 23 DWT coefficients, RR_1 and RR_2 are called as feature vector.

3.3 Classifier: Neural Network

Back propagation is a systematic method for training multilayer artificial neural networks & provides a computationally efficient method for changing the weights in a feed forward network, with differentiable activation function units, to learn a training set of input-output examples. The backpropagation neural network is used as decision maker classifying arrhythmias is a complicated problem, to solve this two hidden layer are taken [13]. The input neurons are equal to the input vector size, and output neurons are equal to number of arrhythmias are going to classify. The number of hidden neurons are chosen according to the problem. Activation of the neurons should have several important characteristics: It should be continuous, differentiable, and monotonically non-decreasing. Furthermore, for computational efficiency, it is desirable that its derivative be easy to compute. In this work all neurons uses sigmoid activation function is given by Equation (1)see, Fig.4:

$$f(sum) = \frac{2}{1+\exp(sum)} - 1 \qquad (1) \qquad \text{(Refer [13])}$$

The initial weights to be used in supervised learning for multilayer feed forward neural networks has a strong influence in the learning speed and in the quality of the solution obtained after convergence. Rumelhart made a confident statement: for many tasks, `the network very rarely gets stuck in poor local minima that are significantly worse than the global minima. According to them, initial weights of exactly 0 cannot be used. Moderate values of learning rate (α) and momentum (μ) are chosen.

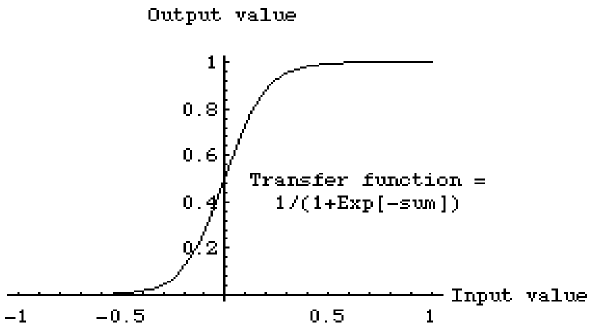


Fig.4: Sigmoid activation function [16]

A target vector was arranged as the desired output for each class. Accompanying each record in the MIT/BIH database in an annotation file in which each heart beat has been identified by expert cardiologist annotators. This annotated information is employed for designing the target vector.

The weights are updated for every training vector, and the termination condition is that the sum square error (E) reaches a minimum value. The connection weights are randomly assigned at the beginning and progressively modified to reduce the overall system error. The weight updating starts with the output layer and progresses backward. The weight update is in the direction of 'negative descent', to maximize the speed of error reduction.

IV. RESULTS

In the present work 10 ECG records with normal beats and different types of arrhythmias are selected from the MIT-BIH arrhythmia database [15]. Only one channel ECG signal with length 30 min was considered and the annotated information of the test data shown in the Table I is used as reference for evaluating the performance of the proposed methods. The effectiveness of proposed method was determined by the Accuracy of an ECG classifier [6] is given as:

$$\text{Accuracy}= \frac{\text{Total number of beats correctly classified}}{\text{Total number of beats tested}} \quad (2)$$

4.1 DWT Approach

The DWT approach is tested with three different types of beats. Feature vectors are calculated by the proposed DWT approach also DWT coefficient of the ECG signal with Noise free and Noisy shown in Fig.5 Training vectors play an important role in classification performance of the ANNs with supervised learning, i.e., supervised learning neural network with large amount of training data gives good performance. In this work feed forward neural network with two hidden layers are taken. Sigmoid activation function (see, Equation .1) is used for all neurons. Set α = 0.000055 and μ =0.00825

TABLE I

Description of the annotated ECG test data for reference from the MIT-BIH arrhythmia database

Record	NB	LBBB	RBBB
100	2237	0	0
101	1858	0	0
103	2080	0	0
106	1505	0	0
109	0	2490	0
111	0	2121	0
118	0	0	2164
123	1513	0	0
124	0	0	1529
207	0	1457	85

4.2 Accuracy

The experimental result in term of Accuracy for proposed method are listed in table II

TABLE II
Classification and Accuracy for Arrhythmia Data Set (NN classifier)

Observations	Normal beat	LBBB beat	RBBB beat	Total
Total No. of beat	9143	6068	3778	18989
Correctly classified	9141	6054	3766	18961
Unclassified	2	28	12	60
Overall Accuracy				99.85 %

The result indicate that NB, LBBB, RBBB are classified with good Accuracy. The overall accuracy of the classification has been observed to be 99.85%.

4.3 Noise Considerations

The ECG signals initially used for classification are noiseless. The overall picture is not complete however unless noisy ECG signals are considered. It is expected that any ECG recognition system will have to operate in a noisy clinical environment. There are two major concerns in this area. The first is related to how the recognition performance of the basic system designed for clear data performs when the input data is now no longer noiseless.

The noise is generated as a random signal and the amplitude of the noise is varied to give a range of signal to noise ratios (SNRs). It would be expected that the addition of noise to the original ECG signal would cause the recognition performance decreases. A random function is used to produce the noise signal. The SNR is determined for various noise powers. The SNR is determined as:

$$\text{SNR}=10\log10\frac{\text{Sum square of ecg signal}}{\text{sum square of the noise}} \qquad (3)$$

The required SNR is selected by adding the appropriate percentage noise to the ECG signal. The ECG signal almost corrupted, noise has been added to all frequency components. The performance of the proposed methods are tested with these noisy ECG signal. In noisy ECG record is given as input to DWT. The results show that classification rate of the classifier decreases by adding noise to the signal. The second consideration is how the basic recognition system can be modified so that the effects of noise are minimized. In second approach, the eight set of ECG record of MIT-BIH database were used and sampling frequency is set to 360 and added with 50Hz power line interference noise with 0dB SNR. The Butterworth digital IIR filters are used for noise removal. For this part, the experimental results in terms of accuracy for arrhythmia recognition of the different records are listed in Table III

TABLE III
Performance of the NN classifier

Record	MIT-BIH Normal	NN Normal	MIT-BIH LBBB	NN LBBB	MIT-BIH RBBB	NN RBBB	Accuracy %
100	2237	2237	---	---	---	---	100
101	1858	1667	---	---	---	---	89.72
103	2030	2030	---	---	---	---	100
106	1505	1446	---	---	---	---	96.08
123	1513	1512			---	---	99.93
109	---		2490	2372	---	---	95.26
111	---	---	2121	2102	---	---	99.71
118	---	---	---		2164	2149	99.30

The results indicate that NB, LBBB, RBBB are classified with good accuracy. The overall accuracy of the classification has been observed to be 97.5%.

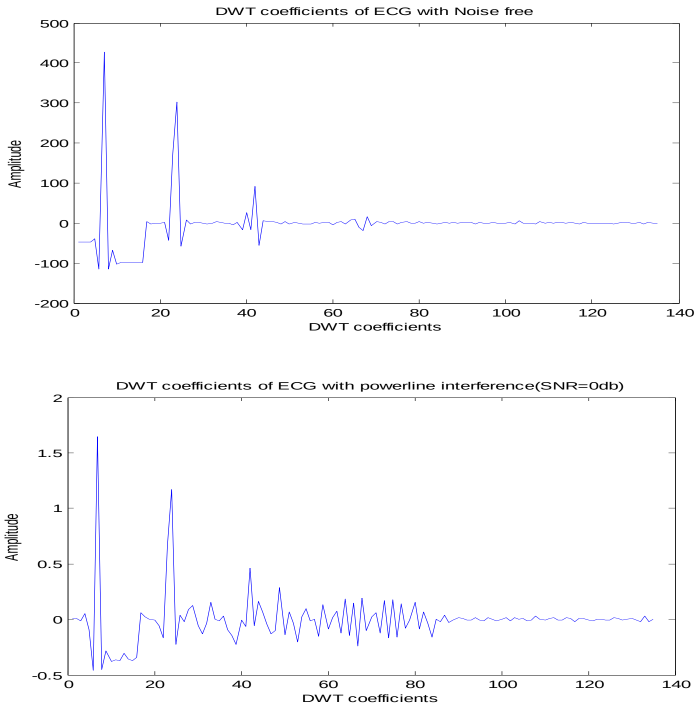


Fig. 5: DWT coefficient of the ECG signal with (a) Noise free, and (b) Noisy

4.4 Comparison

We have compared our methods with the results presented in the literature by using different methods of beat recognition. The comparison will be made to the following beat recognition systems, reported in the international journals: Unsupervised Soft Competitive Learning (USCL) neural network [6], Fourier Transform Neural Network (FTNN)[7], and Discrete Wavelet Transform (DFT1) [8]

TABLE IV
Comparison of different ECG Classifier

Method	No. of beat types	Accuracy
DWT	3	99.85
USCL	5	98.02
FTNN	3	98
DFT1	10	89.4

Table.IV summarizes the comparative results of the accuracy of beat classifiers presented above. The comparison indicates good accuracy of the proposed methods

V. CONCLUSIONS

In this work an arrhythmia classification system using ECG signals based on Artificial Neural Network and wavelet transform is presented. Using wavelets (Sym7) ECG signals is decomposed upto 4^{th} level and then its features are extracted. Which gives the accurate and precise change in the shape of ECG compared with the other transform domains like Fourier transform. A high quality of feature set is important factor for good performance of ECG analysis algorithms. In this approaches, `sym7' wavelet takes care of the discontinuities at the edges. The selected features from the wavelet transform are given as input to the supervised back propagation neural network with two hidden layers for classification. The accuracy is found to be 99.85 % for DWT approach.

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