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WAVELET BASED FEATURE EXTRACTOR AND ANN BASED CLASSIFIER FOR OPTIMAL ECG INTERPRETATION

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Abstract: The heart plays the most vital role of supplying nutrients and oxygen in any organism. Any abnormality in its function renders the body to many complications which may sometimes even lead to death. Hence, timely and early diagnosis of any abnormality is extremely important. Another requirement of the hour is the Automatic detection. Several techniques have been developed till date, but efficiency achieved so far leaves room for improvement. This paper also, presents a technique that aims at automatic detection of cardiac abnormality using an Artificial Neural Network. The detection is done on the basis of the wave shapes of different QRS complexes for different arrhythmias which are extracted from the ECG beats using Wavelet Transform. As the Daubechies wavelets are similar in shape to the QRS complex of the ECG, db4 has been used in the above context. The performance accuracies achieved for training, testing known data and unknown data have been found to be 99.7%, 99.2% and 96.2% respectively. The MIT-BIH database has been used for the present study and an altogether of seven different beats have been used for classification.

Keywords: *Arrhythmia, QRS Complex, Artificial Neural Network, Cascade Neural Network, Wavelet Transform*

1. INTRODUCTION

Cardiac Diseases are one of the leading killers all over the world. Thus, early diagnosis and quick treatment of these arrhythmias are the need of the hour. Preliminary examination is basically done by interpreting the ECG which is a two dimensional plot of the electrical activity of the heart where the x-axis represents the time in milliseconds and y-axis represents amplitude in millivolts. The electrical activity portrays the mechanical activity of the heart. Hence, any abnormality can easily be detected in the ECG [1]. But growing number of cardiac patients has made it inevitable for the scientists and engineers to develop some automatic interpretation techniques which could not only assist but also share the load and pressure on the physicians. Several automatic interpretation techniques have been developed since then, whose performance accuracies depended on the type of application and, Artificial Neural Network (ANN) is one of them. But the advantage of ANN over other techniques is that it is tolerant to imprecision and as computing is done parallelly, the system never crushes at once, and instead the performance degrades slowly which can be detected easily for necessary action [2, 3]. An ANN can be trained with some parameters which are specific to a particular class and can be used to identify the same class later on based on the knowledge acquired by the network during its training. Therefore, these networks can be used for purposes like, clustering, classification or pattern recognition [3].

2. MOTIVATION

The Heart is a wonderful organ. It beats at rate of 70-100 beats per minute. Any deviation from these figures leads to different heart disorders which might be sometimes very dangerous. Therefore, early diagnosis is a must. But in a country like India where population is very huge and number of cardiac patients growing day by day, physicians are put into much pressure and work load. Thus, in this situation, there is a need to develop some automatic ECG interpretation techniques which could not only assist the physician but also share his/her work load. As already mentioned, ECG displays the electrical and hence, the mechanical activity of the heart. So, any deviation from the normal rhythm can be easily and clearly noticed in it. And for classification of these beats, ANN based interpretation techniques are very much in trend because of its property of being tolerant to faults. Keeping these factors in mind the presented research has been carried out.

3. METHODOLOGY

Detecting a particular Arrhythmia is mostly depended on the proper reading of the ECG waveform. The ECG have certain segments like the P wave, QRS complex, T wave, PR interval etc. which conveys information regarding various activity of various portions of the heart. The QRS complex portrays much of the information regarding the functioning of the heart. Most of the arrhythmias can be detected just by studying the QRS complex itself of the ECG waveform. Therefore, in the present method effort has been put in extracting the QRS complex of heart beat using a time-frequency based technique called the Wavelet transform. The technique decomposes the signal into high and low frequency components. The high frequency components are called detailed coefficients whereas the low frequency components are called the approximate coefficients. This process can be continued to decompose the approximate coefficients of the first level to obtain the detailed and approximate information of the next level and so on. Figure.1. shows the schematic of the wavelet decomposition. Here 'S' is the signal, 'cA1' and 'cD1' are the approximate and detailed coefficients at the first level respectively and so on [4, 5]. Selection of the appropriate wavelet and the number of levels of decomposition depend on the application and the feature to be extracted. In the present study Daubechies wavelet, db4 has been selected as the mother wavelet. This is because daubechies wavelet family is similar in shape to the QRS complex [6, 7].

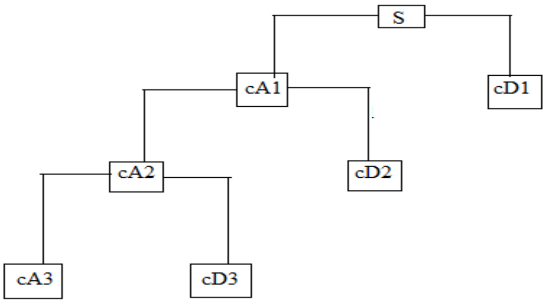

Fig. 1: Schematic of the wavelet multilevel decomposition

The database used is MIT-BIH database. Seven patients have been considered for seven different types of ECG beats and the beats are: Normal (N), Right bundle branch block (RBBB), Left bundle branch block (LBBB), Premature ventricular beat (PVC), Paced beats (PB), Ventricular flutter (Vf) and Atrial premature beat (APB). Patients considered for the beats are given in the table.1. below.

Table.1: Patients considered for the different abnormalities

Sl.No.	Type of beat	Patient numbers
1	Normal (N)	100
2	Right bundle branch block (RBBB)	212
3	Left bundle branch block (LBBB)	109
4	Ventricular premature beat (PVC)	200
5	Paced beats (PB)	107
6	Ventricular flutter (Vf)	207
7	Atrial premature beat (APB)	232

The record of one minute for each patient has been taken and the particular beat that has to be studied is sorted out. The R peak of that particular beat is placed at the 151^{st} position of an array of 301 samples i.e. exactly at the middle of the array [8, 9, 10]. In this way a matrix for each type of beat is formed which consists of 301 columns and number of rows equal to the number of that beat present in the record of that particular patient.

The algorithm goes like this:

1. Matrix of one type of beat is taken at a time where each row represents a beat (one complete cardiac cycle). Fig.2. shows plot of such a beat of normal pattern.
2. Each beat is decomposed by db4 to 4^{th} level and the approximate coefficients of the 4^{th} level are used to generate the wave which now has lesser number of coefficients than the original signal. Hence, the wave had to be reconstructed again to have the same number of coefficients as in the original waveform using zero padding. This assures the position of the R peak at the 151^{st} position in the reconstructed signal. The new signal waveform is named S1. Fig.3 shows S1.
3. Above step is repeated, for decomposition upto 6^{th} level and the new waveform generated is named S2. Fig.4 shows S2.
4. Signal S3 is generated by subtracting S1 from S2. Fig.5 is the plot of S3.
5. Power of S3 is raised to 4 to highlight the QRS complex and thus it is extracted which is shown in fig.6.

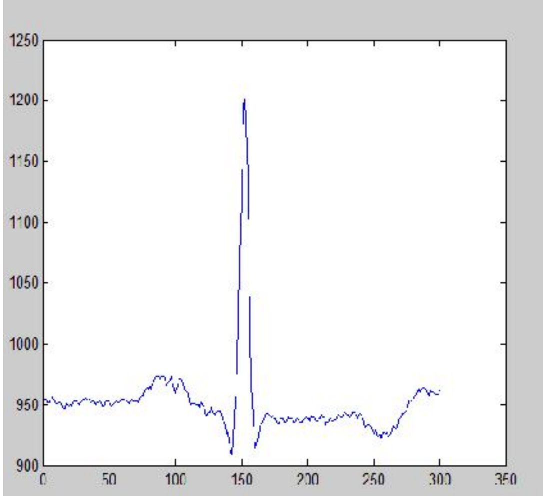

Fig.2. Plot of one beat of original Normal ECG wave

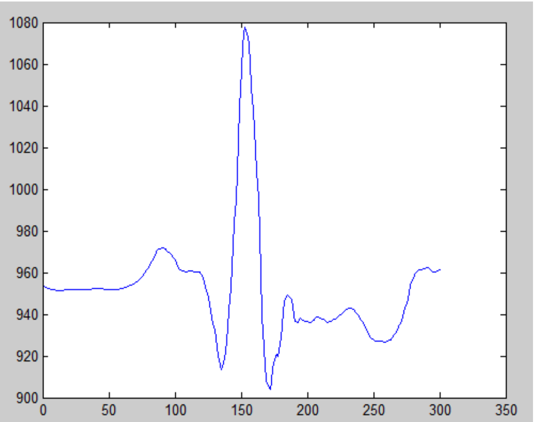

Fig.3. Plot of Approximate coefficients of db 4 level 4 wavelet transform after reconstruction

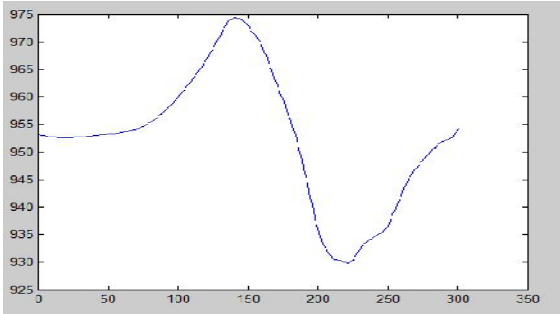

Fig.4: Plot of reconstructed wave of approximate coefficients of db 4 level 6

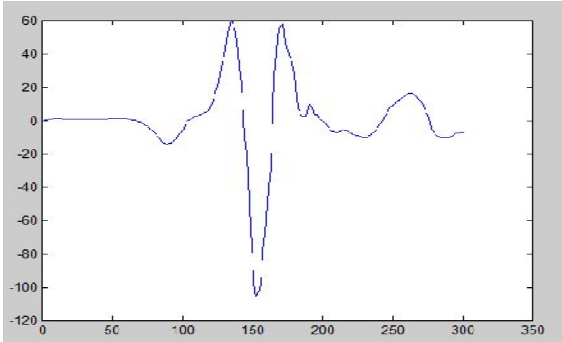

Fig.5: Plot of subtracted waves of level 4 from level 6

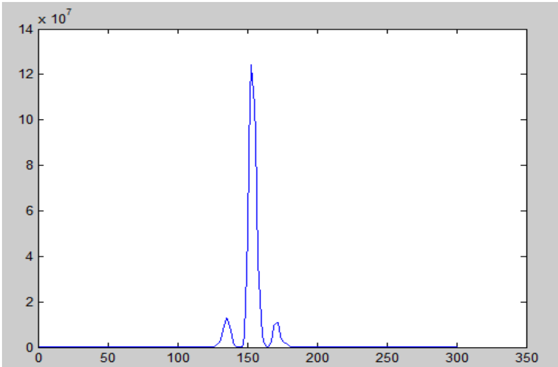

Fig.6: Plot of extracted QRS complex

Thus, a matrix of QRS complex extracted beats is generated. This matrix is used as input to the network for training [11]. The network used is a cascade network which has one hidden layer of 5 nodes and 35 input nodes that represent the QRS complex. A general cascade network is shown below which has two hidden layers. A Cascade network has N number of layers with first layer having weights from the input layer and each subsequent layer having weights coming from previous layers as well as the input layer. At first only input and output nodes are used. When no appreciable reduction in the error occurs a hidden unit is added and the network is trained independently and checked for the error. When again no appreciable reduction in error occurs another hidden unit is added and so on. Once installed the hidden unit input weights are frozen while the weights to the output units are retrained. This process is repeated with each additional hidden unit which receives input connections from both inputs and all previous hidden units resulting in a cascade structure [12, 13]. Fig.7 below shows the learning process of a cascade neural network.

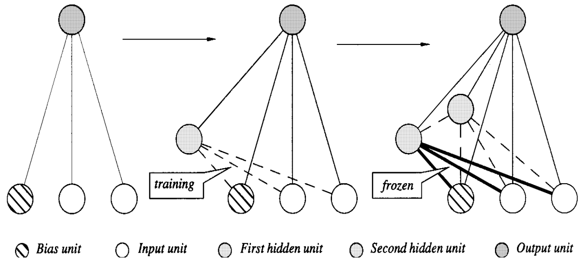

Fig7. A General Cascade Forward Network with two Hidden layer and an output layer

Table.2: Arrangement of dataset in this technique

Sl. no.	Pattern type	Training set	Known testing set	Unknown testing set
1	N	[35 X 100]	[35 X 20]	[35 X 11]
2	RBBB	[35 X 112]	[35 X 33]	[35 X 10]
3	LBBB	[35 X 105]	[35 X 42]	[35 X 9]
4	PVC	[35 X 80]	[35 X 42]	[35 X 4]
5	PB	[35 X 88]	[35 X 42]	[35 X 8]
6	Vf	[35 X 80]	[35 X 42]	[35 X 4]
7	APB	[35X 80]	[35X 43]	[35 X 7]

4. IMPLEMENTATION IN MATLAB

The cascade network has been constructed in MATLAB R2010a. The training and testing of the network for classifying different arrhythmias have been done using backpropagation algorithm. The performance function selected is MSE (mean square error) and activation functions used are 'tansig' in hidden layer and 'logsig' in output layer [14].

5. RESULTS

Results of the presented method, i.e. classification of the various beats using the QRS complex, extracted by the wavelet transform, in terms of a) accuracy and b) sensitivity is given in table 3.

In mathematical form:

$$\textit{Accuracy} = \frac{\text{Number of beats classified correctly in a category}}{\text{Total number of beats present in that category}} \times 100\%$$

$$\textit{Sensitivity} = \frac{\text{Number of beats classified correctly in a category}}{\text{Total number of beats classified in that category}} \times 100\%$$

a) Table.3. Performance in terms of accuracy

Sl. No	Type of beat	Training matrix accuracy (%)	Known test matrix accuracy (%)	Unknown test matrix accuracy (%)
1	Normal	100	100	100
2	RBBB	100	100	100
3	LBBB	100	100	100
4	PVC	100	100	100
5	PB	100	100	100
6	Vf	97.5	95.2	50
7	APB	100	100	100

b) Table.4. Performance in terms of sensitivity

Sl. No	Type of beat	Training matrix sensitivity (%)	Known test matrix sensiti vity (%)	Unknown test matrix sensitivity (%)
1	Normal	100	100	100
2	RBBB	100	100	100
3	LBBB	100	100	100
4	PVC	98.8	97.7	66.7
5	PB	98.9	97.7	100
6	Vf	100	100	100
7	APB	100	100	100

6. DISCUSSIONS

The above result shows that all the beats except the Ventricular flutter wave show 100% performance accuracy. The sensitivity test shows that the misclassification of the Ventricular flutter beats have been done with Paced beats and Ventricular premature beats. This can be attributed to the fact that in all these beats the excitation is generated somewhere in the ventricles itself rather than being transmitted through the AV node. Since, the classification is done on the basis of the QRS complex only, this sort of confusion by the network is quite justified.

7. CONCLUSIONS

By looking at the results it can be concluded that the network is excellent for classifying all the beats except the Ventricular flutter beat using the QRS complex itself. The performance of Ventricular flutter beat is low, as the network confuses it with Premature Ventricular Beats and Paced Beats owing to the fact that they all originate at the ventricles itself. Thus, it can be concluded that for such beats more features has to be considered which can distinctly differentiate them from each other for classification.

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