Denoising and Analysis of ECG Signal using Wavelet Transform for Detection of Arrhythmia

Shilpa Hudnurkar, Ankita Wanchoo

Abstract: ***Electrocardiography is fundamental in the observation of heart function and diagnosis of diseases related to it. It involves measurement of very small bioelectric signals (in millivolts) produced by the human heart during its opening and closing of valves in atria and ventricle and is represented on a scaled paper. P, QRS, and T wave annotations by cardiologists then help in the diagnosis of the patient. Due to the electrical activity of muscles (EMG), instability of electrode-skin contact and patient movement, the noise gets induced during the plotting of the electrocardiogram (ECG). It is important to remove the noise from this signal as it is a signal having very small amplitude and different frequencies repeated almost every second. For such nonstationary biosignals, Wavelet Transform (WT) can be used. In this study, Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) are used to denoise and extract features from the ECG, respectively. The features extracted from DWT are used as input to Artificial Neural Network (ANN) for the classification of normal and abnormal ECG. Abnormal ECGs are further classified into tachycardia and bradycardia. The results show that ANN can classify ECGs with high accuracy. The data used for this study is from the MIT-BIH Arrhythmia Database Directory.***

Keywords : ***Arrhythmia, ANN, CWT, denoising, DWT.***

I. INTRODUCTION

The rhythm of the human heart indicates liveliness and fitness. When the heart loses its rhythm, it is called arrhythmia. Tachycardia is a condition when the heart beats faster than normal, and when it beats slower than normal, it is called as Bradycardia [1]. Arrhythmia may lead to complications as stroke, heart failure, and Alzheimer's disease and hence early detection of the same is of prime importance. Electrocardiography is a cheap, non-invasive basic test for observation of the electrical activity of the heart. Doctors advise this test to the patients having high BP, diabetes, chest pain, etc. Cardiologists diagnose heart-related diseases by observing the electrocardiogram (ECG) which is a representation of periodic opening and closing of valves in atria and ventricle during the very small time. These bioelectric signals have a very small amplitude in millivolts and frequency ranges from 0.05Hz to 100Hz [2]. Their representation on scaled paper is annotated by cardiologists for diagnosis.

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Fig. 1 shows an ideal ECG waveform on a scaled paper. Each small square of 1mm represents 0.04 seconds on the X-axis and 0.1mV on the Y-axis [3]. It is plotted on a paper that runs at the speed of 25mm/s. Fig. 1 also shows P, QRS, T, and U.The P wave represents left and right atrial depolarization, shown as a series of 3 waves, Q-R-S is known as the QRS complex represents ventricular contractions (both right and left), and T-wave reflects the period of ventricular repolarization. [4], [5]. This waveform is periodic and the distance between any two peaks gives heartbeat rate. The distance between two R peaks is calculated for heartbeat rate, and normally it is 60 to 100 bpm (beats per minute).

ECG processing consists of denoising the waveform, extracting features and classifying it as normal or abnormal. ECG contains important information and that is why the signal should be clean. Various noise sources such as power line interference, baseline wander, noise due to respiration, make it difficult to annotate the ECG. Many denoising techniques have been used for ECG signal as the noise caused by different sources lies in different frequency ranges. E.g. baseline wander has very low frequency and EMG electromyogram. [6], [7].

Continuous Wavelet transform (CWT), a technique to analyse a signal simultaneously in time and frequency domain with good resolution has attracted researchers to use it for biomedical signals as ECG. Discrete Wavelet Transform (DWT), a sampled version of CWT has been used by many researchers for denoising [1], [8], [9] feature extraction ([2], [5], [7] and detection of QRS complex [10] of ECG signal. For the classification of ECG, different architectures of Artificial Neural Network (ANN) are used by many researchers e.g. [11] used Multi-Layer Perceptron (MLP) ; [12] used MLP; [13] used Back Propagation Network (BPN), Feed Forward Network (FFN) and MLP, [14] used Probabilistic Neural Network.[7] used k-NN for the classification. However, each of them differs in the methods of denoising extracted ECG features and training and testing datasets used in the study.

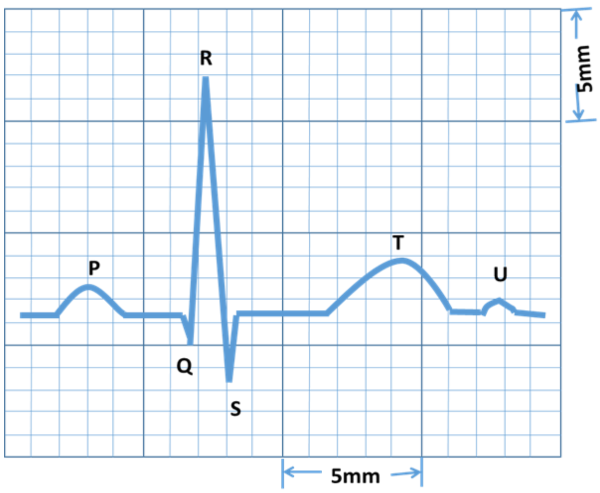

Fig. 1.An ideal ECG waveform on scaled paper

In this study, CWT is used for denoising, DWT for R peak detection and R-R interval detection and Feed Forward Neural Network is used for classification of normal and arrhythmic ECGs. The paper is organized as follows: section 2 gives methodology, in section 3 experimental work is described, section 4 summarizes the results and section 5 concludes the work.

II. METHODOLOGY

The ECG signals data source for this study is the MIT-BIH arrhythmia database [15]. 28 ECG signals of 10-second duration each are downloaded as .mat files. MATLAB 2016 is used for implementing CWT, DWT, and ANN. The ECG signal is sampled at 360 Hz.

The steps followed are:

Step1: CWT of the ECG signal is plotted. The scales used are from 1 to 48.

Step2: For all the scales, CWT coefficients are exported to the excel sheet. By applying soft thresholding to all the coefficients signal is denoised.

Step3: CWT of the denoised coefficients are taken and plotted.

Step4: DWT is then plotted for 4 levels of approximations and details. R peaks and distance between two R peaks are exported to an excel sheet.

Step5: For each waveform, these features are obtained. Feed Forward Neural Network (FFN) is used for classification. Out of 28 records, 19 records are used for training the network and the rest of them are used for testing.

Step 6: Interpretation of results.

The flow chart of the methodology is as given in Fig. 2

III. EXPERIMENTAL WORK

The data acquired from the MIT-BIH database is in the form of .mat files. Hence it is processed to obtain basic ECG waveform for all the records. ECG waveform for the first record no. 100 is as shown in Fig.3.

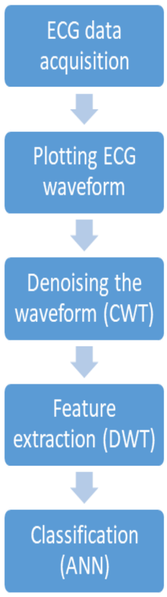

Fig. 2.Methodology flow chart

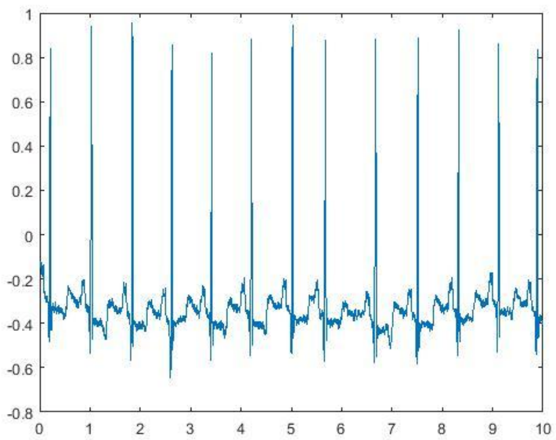

Fig. 3.ECG waveform of record no. 100

A. Denoising

Earlier, ECG signals were analyzed in the frequency domain using Fourier Transform and Fast Fourier Transform techniques. These methods fail to provide information about the frequency present at a particular time. Filtering techniques such as IIR notch filter, FIR filter, adaptive filters have been used to remove power line interference from ECG signal [6]. These filtering techniques work well with stationary signals [16]. Wavelet Transform represents the signal in both time and frequency domains simultaneously [17] and is suitable for analyzing and denoising nonstationary signals. In CWT the signal is multiplied by scaled and shifted versions of the wavelet function Ψ and summed over time.

$$C\ (scale,\ position) = \int f(t)\ \Psi(scale,\ position),t)\ dt \quad (1)$$

where Ψ is a mother wavelet

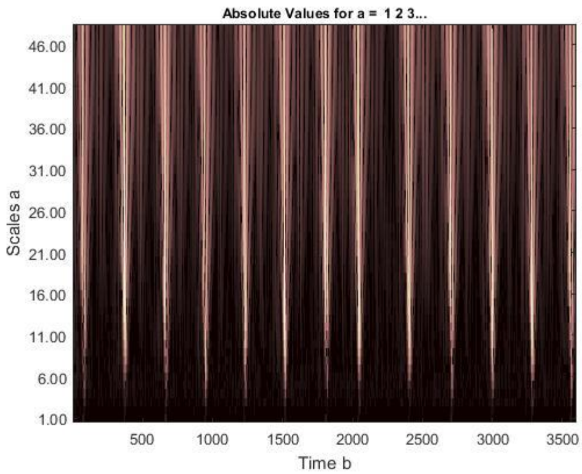

Fig. 4.Continuous Wavelet Transform of record No.100

that is compressed and expanded on different scales. CWT returns coefficients which are a function of scale and position [1]. Mother wavelet can be selected from different wavelet families and here db4 is chosen as mother wavelet. The CWT for each waveform is plotted. One waveform for record number 100 is shown in Fig.4.

The wavelet toolbox can also be used to plot CWT and for the first record, it is used and is as shown in Fig.5. Signal analysis can be performed using toolbox, however, for denoising, sampled version of CWT i.e. DWT is used. Being continuous, CWT gives coefficients for each scale for which CWT is calculated and hence when coefficients are plotted it shows where there is a change in frequency with respect to time. In this study, all the CWT coefficients are used and soft thresholding is applied to all the coefficients. Instead of plotting 3D, the 1D plot of noised and denoised signal is obtained and is as shown in Fig. 6 a and b respectively.

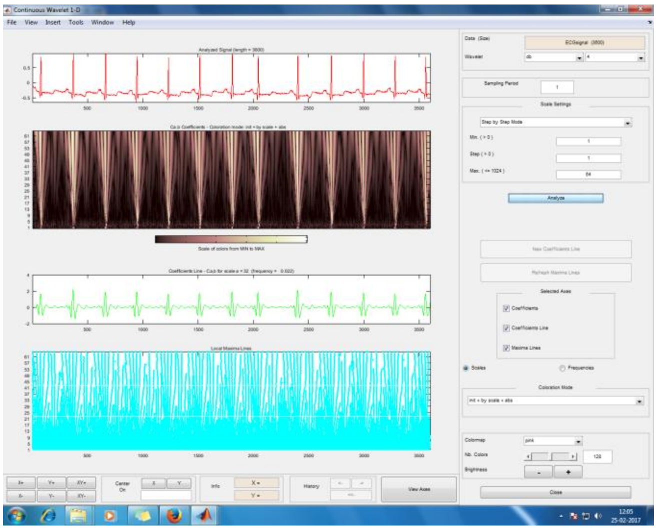

Fig. 5.Continuous Wavelet Transform of record No.100 using Wavelet Toolbox

B. Feature extraction

Discrete Wavelet Transform of the ECG waveforms is plotted using a wavelet toolbox. For this db4 wavelet is used and 4 levels of approximations are used. Four details and the fourth approximation are shown the Fig. 7. A function is used

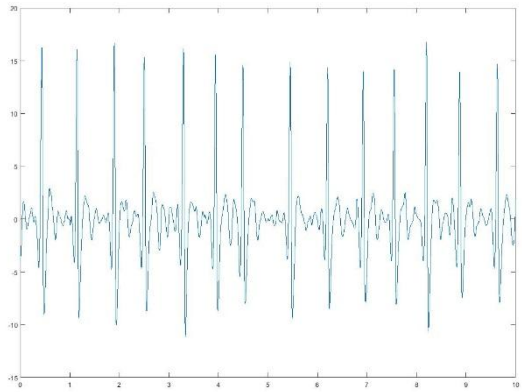

Fig. 6.a. ECG with noise

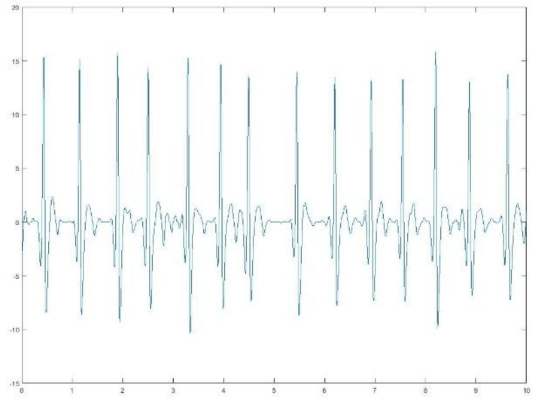

Fig. 6.b.ECG denoised

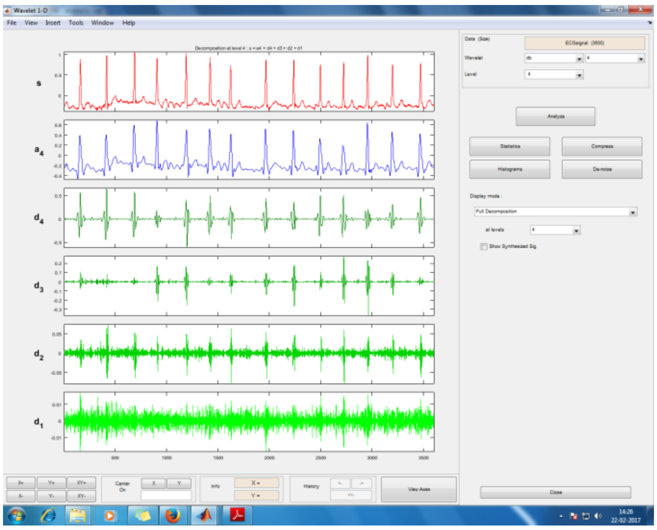

Fig. 7.DWT of record no.100 using wavelet toolbox

for R-peak detection [18]. The peaks are shown in red circles in Fig. 8. The distance between the peaks is also found out and these two features are exported to separate excel sheets. The location of the peaks is used for the classification of the ECG waveforms. For the R peak detection inverse CWT (ICWT) waveforms are used.

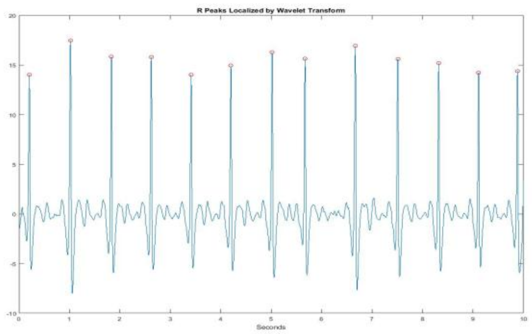

Fig. 8. R- Peak detection record no. 100

C. Classification of ECG waveforms

For the classification of ECG waveforms, ANN's FFN is used. As shown in Fig. 9, the neurons (blue circles) are combined to form three layers: input, hidden, and output. It is a feed-forward network because, when fully connected, the output of each neuron in a layer acts as an input to all the neurons in the next layer, with no neuron sending outputs to neurons in their own layer or any previous layers. It is a supervised network in which the network is trained with certain data set giving expected output. The network tries to minimize the difference between expected output and network output. For achieving this, it uses an algorithm specified by the user. Once trained, it is tested for unseen data set.

For this study, a number of nodes/neurons in the hidden layer are selected as 18 and the single hidden layer is used. Out of 28, 19 records are used as inputs for training the network. Remaining records are used for testing. For training, the network ideal R-R interval in seconds is given for Tachycardia, Bradycardia, and Normal ECG. The number of R peaks in 10-second duration is different for all the ECG waveforms. Hence, during training and testing, only nine R-R intervals are used.

Though the number of samples in the training set was small, the regression value (R-value) of the trained network was 0.95. The R-value obtained while training the network is graphically shown in Fig.10.

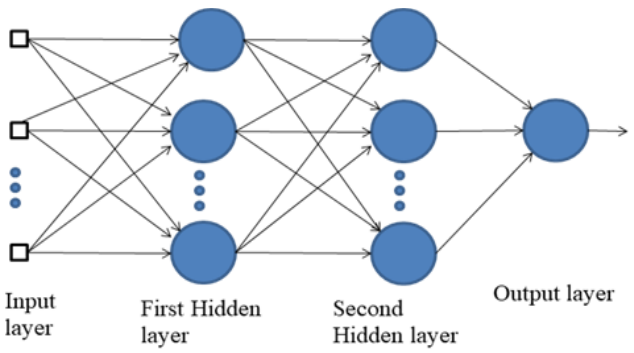

Fig. 9.ANN Architecture

Then, the network was tested for the remaining data set. The results obtained for each waveform were checked for their class. The results obtained are discussed in the next section.

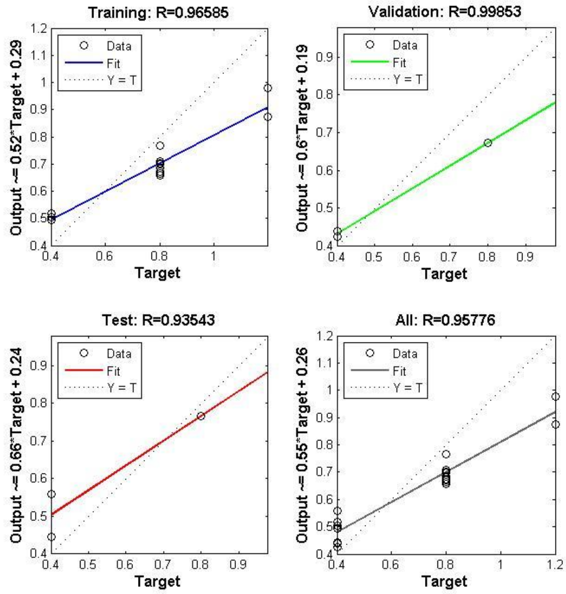

Fig. 10. Regression values after training the network

IV. RESULTS

During the experimental work, CWT was plotted for each ECG waveform and it was observed that each CWT clearly shows the change in frequency at the QRS complex (Refer Fig 4 and 5). The signal denoising which was performed applying a threshold to all the CWT coefficients was found to be time-consuming. In feature extraction step vectors obtained for R-R interval were able to give good time resolution.

Records used in the study are as follows:

Record number: 100 to 109; 112, 113, 115, 201, 203, 205, 207 to 210, 212 to 215, 217,219 and 220. Distribution of records of MIT-BIH arrhythmia database [13] is shown in the Table I.

According to the criteria of 60 to 100 bpm as normal rhythm, greater than 100 bpm is considered as Tachycardia and less than 60 bpm are considered as Bradycardia[19]. From a number of peaks detected during the feature extraction phase, records under the study found to be in the classes indicated in Table II.

R-R interval data for the above records are used for training and testing the ANN. Records that were used for training ANN are from 100 to 209. 210 onwards are used for testing. The results obtained after testing the network are as per Table III.

The results indicate that network architecture selected for this study gave promising results as it was able to classify all the records successfully during the testing stage. This may be because of less the complexity of data used as input and presently only one feature is used for classification.

V. CONCLUSION

ECG processing and the

Table- I: Distribution of MIT-BIH arrhythmia database records selected for this study

Class	Record Number
Normal	100-101-103-105-106-112-113-115-201-202-205-209-213-215-219-220
Abnormal	104-108-109-203-207-208-210-212-214-217

Table-II: Classification of records under study based on number of R peaks

Normal	100, 101,102,103,105,112,113,115,205,209,210,213,215,219,220
Tachycardia	104,106,107,109,203,208,212,214,217
Bradycardia	108,202,207

Table-III: Classification results of FFNN

Normal	210,213,215,219,220
Tachycardia	212,214,217
Bradycardia	None.

classification undertaken in this study employed CWT, DWT, and ANN for denoising, feature extraction, and classification respectively. With wavelet transform, one can analyze nonstationary ECG signals in time and frequency domain simultaneously. In the plot of CWT different frequencies can be easily seen. DWT at the fourth level of approximation was used for feature extraction. It could capture the R peak and also could find the R-R interval. FFN employed for classification gave 100% accurate classification. By extracting more features and training the network for those features would be able to further classify ECG signals in more than two classes.

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