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An Approach To Automatically Detect Cardiac Arrhythmia

Priyanka Urban[#1], E.Smily Jeya Jothi[*2]

[#]EIE Department, Karunya University

Abstract*—Electrocardiogram (ECG), a non-invasive technique is used as a primary diagnostic tool for cardiovascular diseases. The main objective is to make the analysis of normal and abnormal beats easy so that the patient could be diagnosed for the heart problems in less time as well more accurately so that medical practitioners have primary information about the ailment and could start a treatment early.. However, it is very difficult to identify the minute changes in ECG signals which indicate a particular type of cardiac abnormality, hence imposing the need for a computer assisted diagnosis tool. A computer based intelligent system for analysis of cardiac states is very useful in diagnostics and disease management. In this work, we propose a methodology for the automatic detection of normal and abnormal cardiac conditions using ECG signals. ECG signals from MIT BIH arrhythmia database were used for analysis and classification. The ECG signals were first denoised using wavelet based denoising technique. After the denoising, it was subjected to QRS complex detection. The QRS complex is physiologically an important peak in the ECG signal. After detection of QRS complex, the ECG was segmented to obtain 200 samples segment as a beat for subsequent analysis. The segmented ECG signal was used for its dimensionality reduction using Principal component analysis(PCA).PCA implementation decreases the training error and the sum of the training and test times. In total 12 components were used for the pattern classification using feed forward neural network. The proposed system is clinically ready to deploy for mass screening programs. Overall, compared to previous techniques, this system is more suitable for diagnosis of cardiac arrhythmia with highest accuracy.

Keywords*— Electrocardiogram (ECG), MIT-BIH arrhythmia database, Neural Network (NN), Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA)

I. INTRODUCTION

Cardiac arrhythmias including heart attack, stroke, and hypertension, is caused by disorders of the heart and blood vessels and is by far the leading cause of death around the world. However, most heart attacks and strokes could be prevented if some method of pre-monitoring and pre-diagnostic can be provided. In particular, early detection of abnormalities in the function of the heart, called cardiac arrhythmias, can be valuable for the clinicians. The electrocardiogram (ECG) plays an important role in the process of monitoring and preventing cardiac arrhythmias. The ECG signal provides key information about the electrical activity of the heart. This electrical activity is related to the impulse that travels through the heart, which determines its rate and rhythm. Physicians use this information to diagnose many cardiac disease conditions. Early ECG systems were just recording the signal by printing it in a paper strip. Slight changes in the amplitude and time of the ECG signal from a predefined pattern have been used routinely to detect the cardiac abnormality. Because of the difficulty to elucidate these changes manually, a computer-aided diagnosis system can help in monitoring the cardiac health status. Computer-aided cardiac arrhythmia detection and classification can play an important role in the management of cardiovascular diseases. The basic complexity and mechanistic and clinical interrelationships of arrhythmias often brings about diagnostic difficulties for treating physicians and primary health care professionals creating frequent misdiagnoses and cross classifications using visual criteria Computerized algorithms can identify cardiac arrhythmias with higher diagnostic accuracy with significant reduction in the cost. Many works reported on arrhythmia beat classification shows that there is a need to improve the classification accuracy when used for huge database. Also most of the methods use complex mathematical features imposing lot of computational burden while evaluating these features. The aim of this paper is to develop a simple methodology for arrhythmia beat classification, with highest diagnostic accuracy even when used for large database. The paper is organized as follows: Section 2 describes the materials and methods used. Classifier

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used is explained in Section 3.We present the experimental results in Section 4.Finally Section 5 conclude the paper

II. MATERIALS AND METHODS

In this work, we have used MIT BIH arrhythmia database [1] for the ECG analysis and classification. The dataset is sampled at 360 Hz. Fig. 1 depicts the proposed methodology of classification of Normal and Abnormal ECG. The working of each block is explained in the following sections.

A. Pre-processing

The pre-processing involves Discrete Wavelet Transform (DWT).Unlike Fourier transform, the DWT offers resolution in both time and frequency domains. The DWT is obtained from the continuous wavelet transform by sampling it on a dyadic grid. The DWT decomposes a signal successively into low frequency and high frequency components. The low frequency component is called approximation, and the high frequency component is called the detail. Fig. 2 depicts the DWT decomposition using filter banks. The ECG signal x(n) is passed through a low pass filter h(n), and then down

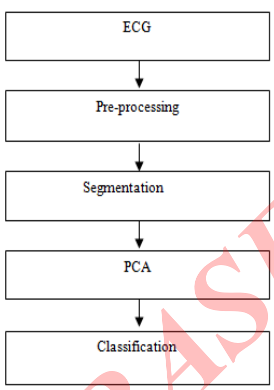

Fig 1 Proposed methodology

sampled by a factor of two to obtain the approximation coefficients at level one. The detail coefficients were obtained by passing the signal through g(n) and then down sampling by a factor of two. The two filters h(n) and g(n) were called quadrature mirror filters. As seen from Fig. 2, the original signal is passed through lowpass, h(n) and highpass, g(n) half band filters and then both signals were down sampled by a factor of two. The low pass signal is again successively filtered by h(n) and g(n) and sub sampled by a factor of two to obtain the next level approximation and detail coefficients. The ECG signal downloaded from MIT-BIH arrhythmia database may contain artifacts, noise and baseline wander. Therefore it is necessary to denoise the ECG signal to remove all these unwanted parts of the signal. First the raw ECG signal was subjected to wavelet based denoising using db6 wavelet[2] .The ECG signal was decomposed up to six levels of decomposition. The necessary sub bands are detail coefficients of 3rd, 4th, 5th and 6th levels. So only these coefficients are retained and all other sub band coefficients are replaced with zeros and inverse wavelet transform is computed to obtain denoised ECG.

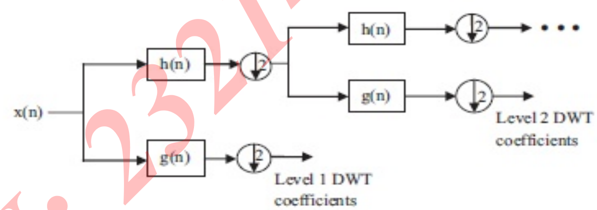

Fig 2 DWT decomposition

B. Segmentation

After denoising the ECG, it is subjected to QRS complex detection using Pan Tompkins algorithm[3]. The algorithm consists of computation of derivatives, moving window integrator, squaring and detection of rising edge of pulses. The derivative provides the slope information of ECG waveform, squaring will emphasize higher amplitudes and suppresses smaller amplitudes and moving window integrator performs averaging operation, thereby removes noise. Fig-3 shows the various filters involved in the analysis of the ECG signal. After detection of QRS complex, 99 samples were chosen from the left side of QRS mid-point and 100 samples after QRS mid-point and the QRS mid-point itself as a segment or beat of 200 samples

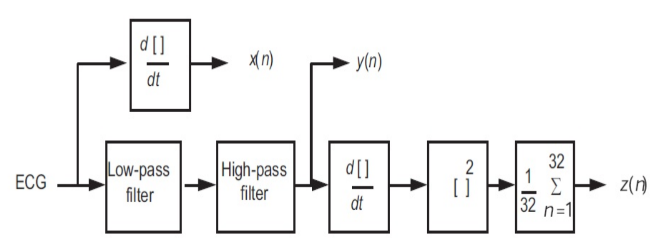

Fig 3 Filter stages of QRS detector

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C. Principal Component Analysis

Principal Component Analysis (PCA) is a linear dimensionality reduction technique that seeks projection of the data into the directions of highest variability[4]. It computes the principal components which are the basis vectors of directions in decreasing order of variability. The first principal component provides basis vector for the direction of highest variability. The second principal component provides the basis vector for the next direction orthogonal to the first principal component and so on. A percentage of total variability of the data is set as the threshold in order to select the number of principal components. Computation of principal components involves computation of covariance matrix of the data, its eigen value decomposition, sorting of eigenvectors in the decreasing order of eigen values and finally projection of the data into the new basis defined by principal components by taking the inner product of the original signals and the sorted eigenvectors

D. Classifier

In this paper a fully connected feed forward neural network (NN)[5] is used as classifier for automated pattern identification. The neural network consists of a layer of input neurons, two layers of hidden neurons and a single layer of output neurons. Random weights are initially assumed and the training data is fed to the neural network to obtain network response. Based on the training labels the difference between the obtained output and desired output by the network is computed and it is called as error signal. Based on this error signal, the weights are updated by back propagating the error. The process is repeated until the training error is below a given threshold. After that the testing data is fed to the trained neural network and the classified output is noted and the performance of classification is computed based on testing labels

III. RESULTS

The ECG signals from MIT-BIH database as input were first denoised using wavelet based denoising technique using db6 wavelet. The signal was decomposed upto six levels of decomposition and the necessary sub bands are detail coefficients of 3rd, 4th, 5th and 6th levels. These coefficients are retained and inverse wavelet transform is computed to obtain denoised ECG

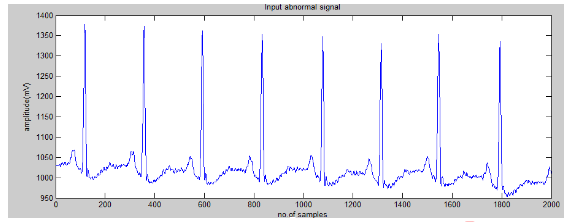

Fig 4 Input abnormal signal

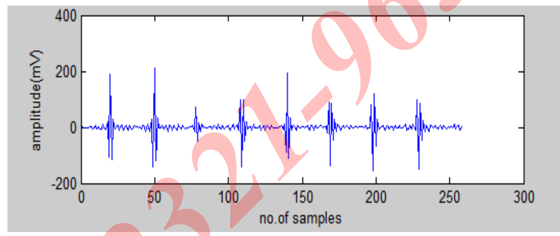

Fig 5 Level-3 detail coefficient

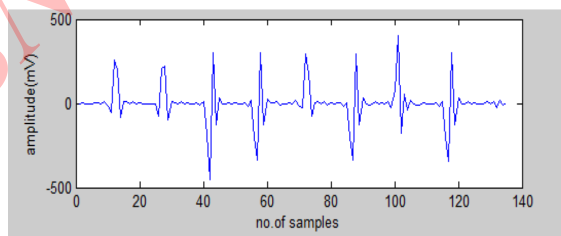

Fig 6 Level-4 detail coefficient

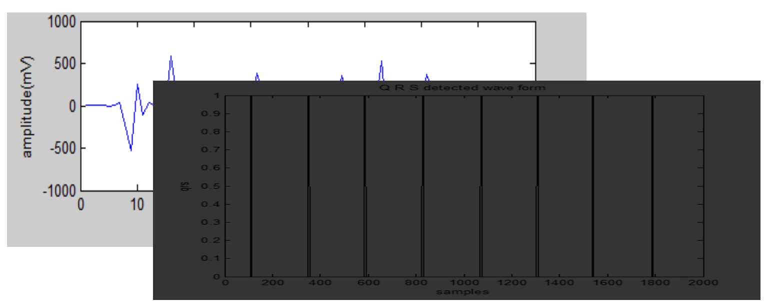

Fig 7 Level-5 detail coefficient

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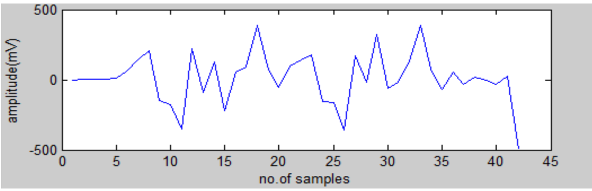

Fig 8 Level-6 detail coefficient

Segmentation involves QRS complex detection. The QRS complex is physiologically an important peak in the ECG signal. Differentiation forms the basis of many QRS detection algorithms. The absolute values of the first and second derivative are calculated from the ECG signal. These two data buffers are scaled and then summed. The summed data buffer is now scanned until a certain threshold is met or exceeded. After detection of QRS complex, 99 samples were chosen from the left side of QRS mid-point and 100 samples after QRS mid-point and the QRS mid-point itself as a segment or beat of 200 samples.

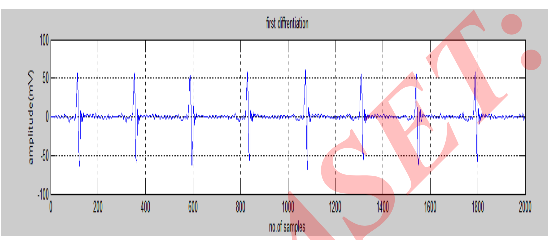

Fig 9 Smoothed and rectified 1st derivative

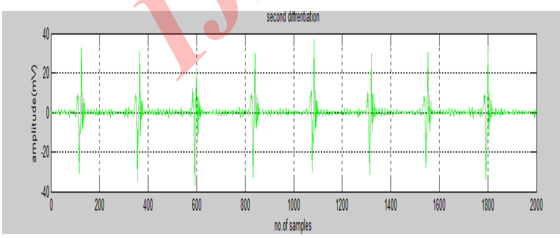

Fig 10 Smoothed and rectified 2nd derivative

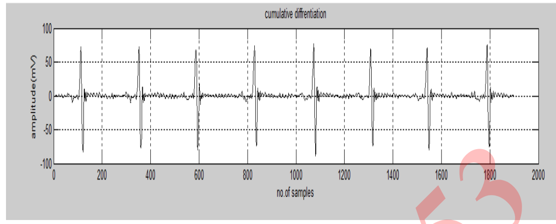

Fig 11 Smoothed and rectified sum of 1st and 2nd derivative

Fig 12 Square pulse output for each QRS complex

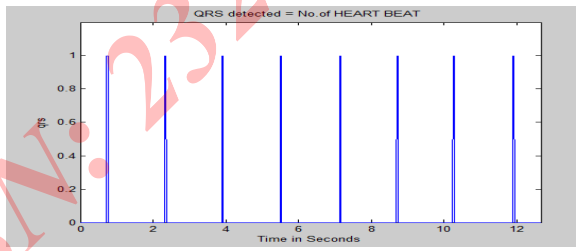

Fig 13 QRS detected in 12sec

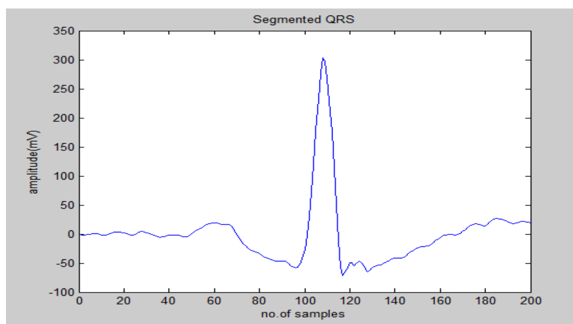

Fig 14 Segmented QRS complex

A huge amount of data is not efficient to perform a pattern recognition process. In our algorithm PCA is applied on the computed matrices of the segmented QRS complex, where each of them is a 14×14 matrix, resulting in 12 principal component (PC) vectors.The principal component values are shown in the table

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TABLE I
PRINCIPLE COMPONENT VALUES

PC1	1.7250
PC2	1.5394
PC3	1.1565
PC4	0.7513
PC5	0.3089
PC6	-0.0034
PC7	-0.1735
PC8	-0.1005
PC9	0.2683
PC10	0.7273
PC11	0.9541
PC12	0.8472

In the current study a fully connected feed forward neural network is used for automated pattern identification. The final MATLAB figure will be displayed as shown in fig-6.13.For abnormal ECG signal it will be displayed as ABNORMAL and for normal ECG signal as NORMAL

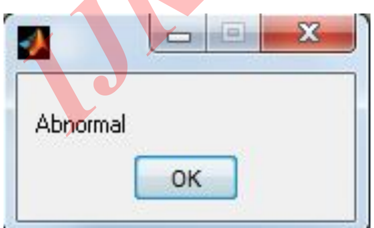

Fig 15 Displayed classification result

A one hidden with 60 layer neurons is created and trained. Fewer epochs means network learns in smaller repetitions it includes 71 iterations. Time required is 0.03sec which means network achieved goal easily and shortly. For the data computation performance is 1.99 e-10 which indicates the final MSE achieved. Lower value of MSE represents higher network accuracy.

IV. Conclusions

ECG signal can be used as a reliable indicator of heart diseases. This project provides an algorithm for accurate detection of QRS complex and automatic classification of cardiac arrhythmias. Feature extraction methodology proves an essential process for reducing the inputs to the classifier drastically. The automatic classification of arrhythmias helps in recognizing the diseases more accurately with less time. This methodology has provided improved results and can be used in practical arrhythmia monitoring systems. It has immense applications in electronic cardiac pacemakers, remote patient monitoring and in intensive care units.

Acknowledgment

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