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Denoising And Classification Of ECG Signal

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ABSTRACT

A condition in which the heart beats with an irregular or abnormal rhythm is known as Arrhythmia. This paper presents a procedure to extract information from Electrocardiogram (ECG) data and determine types of Arrhythmias. Here Empirical Mode Decomposition (EMD) technique is adopted for noise removal and Artificial Neural Network(ANN) is used for classification. The decisions were achieved by determining different intervals such as PR Interval, RR Interval, QT interval etc. and those intervals were compared with the ideal intervals. The ECG records taken from the MIT BIH arrhythmia database are sampled at 360 Hz (fs =360Hz).During the whole process MATLAB was used and ECG signals were taken from Physio Bank ATM.

Keywords:

Denoising, ECG Signal, Artificial Neural Network, Electrocardiogram, Peak detection, QRS Complex.

INTRODUCTION

Electrocardiogram (ECG) signal represents the electrical picture of the heart and being widely used for arrhythmia classification, cardiac diagnosis, etc. The ECG signal acquisition and wireless transmission faces the problem of noise addition to the signal. Addition of noise distorts the morphological structure in the ECG signal. In the earlier reported works, one can find various noises responsible for ECG signal corruption. Power line interference, baseline wander, additive white Gaussian noise (AWGN), etc are to name a few. Therefore, denoising of ECG is required for further processing.

The ECG signal that is used in this paper is part of the MIT-BIH Arrhythmia Database, available online. The database contains 48 records. Each record contains two-channel ECG signals for 30 min duration selected from 24- hr recordings. Header file consists of detailed information such as number of samples, sampling frequency, format of ECG signal, type of ECG leads and number of ECG leads, patient's history and the detailed clinical information.

In this paper noise removal from ECG signal is based on empirical mode de- composition (EMD) and a set of intrinsic mode functions (IMF) is obtained. The main contribution here is adopting Hurst exponent in the selection of IMFs to reconstruct the cardiac signal. This EMD and Hurst-based (EMDH) approach is evaluated in cardiac signal enhancement experiments considering environmental noises with different indices of non-stationarity. Simulation here is done on the MIT-BIH database to evaluate proposed algorithm. Windowing algorithm isused for feature extraction. Experiments show that the presented method offers good results to detect arrhythmia such as Premature Ventricular Contraction (PVC),Paced Beats(PB),Left Bundle Branch Block (LBBB),and Right Bundle Branch Block (RBBB).

AIM

In clinical routine, computer aided diagnosis of cardiac arrhythmias can reduce the workload of cardiologists dramatically enabling them to focus more on treatment rather than diagnostics. Any variation in ECG has to be taken at most care. ECG variations can occur because of noise. This will mislead doctors in diagnosing arrhythmia from normal.

LITERATURE REVIEW

Literature survey report

For arrhythmia classification from ECG signals, first and foremost thing required is a noiseless ECG. So different denoising techniques are available [1]. Each havingits own advantages and disadvantages. Some are complex but gives better performance. So there exist a trade-off between complexity and performance. Here a technique called Empirical Mode Decomposition with hurst based mode is employed for denoising [3] which is comparable with new technologies and can give good performance. EMD can give good result when compared to wavelet domains [2].

The wavelet transform describes a multi-resolution decomposition process in terms of expansion of a signal onto a set of wavelet basis functions. Discrete Wavelet Transformation has its own excellent space frequency localization property. Application of DWT in 1D signal corresponds to 1D filter in each dimension. The input Daubechies Wavelet as mother wavelet is divided into 8 non-overlapping multi-resolution sub-bands by the filters, namely db1, db2, db3up to db8, where db is acronym for Daubechies. The sub-band is processed further to obtain the next coarser scale of wavelet coefficients, until some final scale “N” is reached. When a signal is decomposed into 8 levels, the db6 sub-band signal best reflects the original signal [4].
ECG features such as different time intervals (P,Q,R,S,T) between this points are calculated by windowing algorithm [5]. There are various types of arrhythmia that are life threatening. Automated classification of these malfunctions play a major role in the diagnosis and treatment of the same. This process of classification is done using different forms of algorithms. The algorithms are effective based on their efficiency and time taken for computation. Computation depends on the mathematical model and the procedure involved in analyzing the signal under consideration[6].

For Arrhythmia detection I went through the Time Domain based technique. The technique is followed by ECG signal processing, determination of PR Interval, QRS Interval, QT Interval, ST segment, RR Interval (To determine Heart Rate) followed by Arrhythmia detection via some decision making rules [7]. Cardiac arrhythmias are classified by abnormal activities in the heart. These abnormalities can be analyzed by an electrocardiogram (ECG). Details from this electrical signal can be used to classify what type of arrhythmia, if any, the patient has by analyzing the PQRST wave properties. The arrhythmias analyzed for this study are Bundle Branch Blocks, Paced beats, and Premature Ventricular Contraction. Multiple data samples of normal ECG characteristics also were read by an Artificial Neural Network

(ANN) and analyzed for the differences between a normal signal and an irregular signal[8].

SOFTWARE DESIGN AND DESCRIPTION

Block Diagram

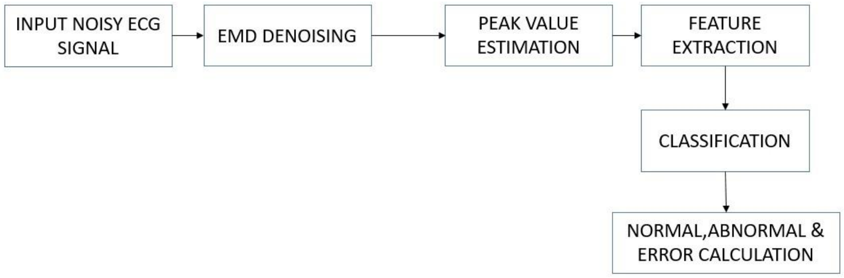

Figure 1: Proposed System

Block diagram of the proposed is shown in the figure. Here noisy ECG signal given as input to the system, which is denoised by Empirical Mode Decomposition. After denoising peaks are calculated and then its features are extracted suchas RR interval, QT interval, PR interval, QRS duration etc. This is given to an Artificial Neural Network(ANN) which classify the arrhythmia.

ALGORITHM

Denoising

On the initial level, the ECG signal is decomposed with the help of EMD methodand it results into a set of IMFs. Further, the Hurst exponent is calculated frame- by-frame for each IMF, to know which of them is mainly composed of noise. Now the reconstruction process is done using the remaining IMFs. For frequency analysis, wavelet decomposition is commonly used. EMD is preferred over other methods because of two reasons. Firstly, the wavelet method needs a set of pre-defined basis functions, and it does not apply to all variants of input signals. Secondly, since wavelet method uses linear time invariant filters therefore it does not work if there are any local variations in the input signal. Whereas EMD analyzes the input signal in an entirely adaptive way and it is completely based onthe local properties of the input signal which makes it suitable for non-stationarysignal analysis. ECG signal is a non stationary signal so EMD can be applied in decomposition of ECG signal. Also the complete reconstruction is assured using the selected IMFs [3].

Peak detection

Next step is the peak detection, in which certain percentage of maximum value set as threshold and comparing with previous and next signal to obtain the peak of ECG signal

QRS Complex

Step 1: ECG signal is read and the length is calculated.

Step 2: The signal is decomposed using db6 wavelet.

Step 3: 3rd , 4th and 5th detail coefficients are selected, as most energy of the QRS complex is concentrated in these coefficients.

Step 4: The wave is reconstructed using detail coefficient 3, 4, 5.(D1=d3+d4+d5)

Step 5: A function d4*(d3+d5) /2n is defined to reduce the oscillatory nature ofthe signal where d3, d4, d5 are the 3th , 4th ,5th detail coefficients and n is the level of decomposition.

Step 6: The threshold value is calculated corresponding to the product of maxand mean of the signal to locate the end points of the moving window.

Step 7: The PQRST peaks are located based on the amplitude of the signal withineach moving window.

Step 8: The time intervals are calculated considering the positions of two consecutive same labeled peaks and stored

Step 9: Diagnosis of various cardiac diseases is done by comparing ground truthconditions with the data [4].

Table 1: Normal ECG Signal Characteristics

Component	Characteristics
Heart Rate	60 - 100 bps
PR Interval	0.12–0.20 sec
QRS Interval	0.06–0.10 sec
QT Interval	Less than half of the R-R interval
ST segment	0.08 sec

windowing algorithm

The windowing algorithm is based on the following:

- The most prominent peaks in an ECG signal are the R-peaks. These peaks are detected by imposing a threshold condition on the amplitude of the signal as shown in Equation $\tau = 0.4 * m$
    - where τ and m denote the threshold and peak value of the signal respectively. The
    - values lying above τ are the R-peaks of the ECG.
- R-peaks occur periodically in an ECG signal. The threshold condition will also give different values in each period containing R-peaks. The particular R-peak in any period is selected by taking the mean of the R values in that period.
- Different periods are selected by finding the difference between consecutive values obtained by the threshold condition. Values in one period are very close to each other and a sharp variation appears as one period ends. That sharp variation is useful in identifying one particular period.

RR Interval

· Once the R-peaks have been identified, RR intervals denoted by t_{rr} are calculated as given by Equation $t_{rr}(i) = (R_{loc(i+1)} - R_{loc(i)})/f_s$

f_s represents sampling frequency (360 Hz) and t_{rr} is used in making windows for the P, Q, S and T waves.

· P and T waves exist in one R-R interval, T waves lie next to the 1st R-peak,and P-waves are present nearer to the 2nd R-peak in one R-R interval.

· The window for the T-wave in one R-R interval is selected by starting from 15% of the R-R interval added to the 1st R-peak location and continuing to 55% of the R-R interval added to the same location.

- The window for the P-wave in one R-R interval is selected by starting from 65% of the R-R interval added to the 1st R-peak location and continuing to 95% of the

  R-R interval added to the same location.

- The particular P and T peak location is selected by taking the highest value in their respective windows.
- The Q-peak is chosen by selecting minimum value in the window starting from 20 ms before the corresponding R-peak and that particular R-peak.
- Similarly the S-peak is chosen by selecting the lowest value in the window starting

  from R-peak to 20 ms after that R-peak. These windows are adaptive because they depend upon R-R interval values and as this interval changes the window will also change.

PR Interval

P-R interval, denoted by t_{pr}, is calculated using following formula

$$t_{pr}(i) = (R_{loc}(i) - P_{loc}(i))/f_s$$

where f_s denotes sampling frequency, R_{loc} denotes R peak locations and P_{loc} denotes P peak locations. The above formula yields an array of t_{pr} values, which are then averaged out to get single t_{pr}

QRS duration

QRS duration t_{qrs} is calculated using following formula

$$t_{qrs}(i) = ((S_{loc(i)} + x) - (Q_{loc(i)} - x))/f_s$$

where x denotes immediate 5 ms, these samples are added to S_{loc} and are sub- tracted from Q_{loc} because QRS duration is defined from start of Q peak till endof S peak as shown in Figure. S_{loc} and Q_{loc} denote S and Q peak locations respec- tively. This formula gives an array of t_{qrs}, which are then averaged to get single t_{qrs}

QT Interval

QT interval t_{qt} is calculated using following formula

$$t_{qt}(i) = (T_{loc(i)} + (t_{rr(i)} * 0.13) - (Q_{loc(i)} - x))/f_s$$

T_{loc} indicates T peak locations. 0.13 Factor is multiplied with t_{rr} and added to T_{loc}, it has same effect as addition of 5 ms. Particular t_{qt} value is selected by taking mean of all values of an array

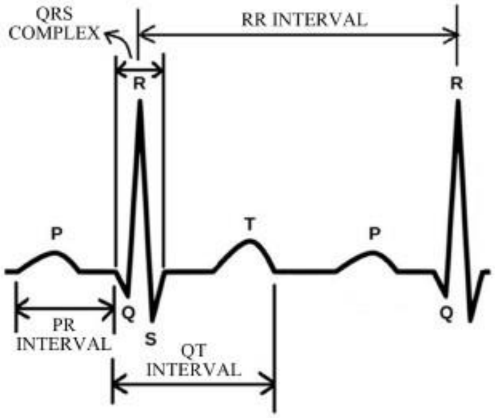

Figure 2: Intervals defined for PQRST wave

Artificial Neural Network

Figure shows the block diagram of Artificial Neural Network. The analysis of this data is done by an artificial neural network. An ANN is a computer network consisting of artificial neurons that are used to solve problems without creating.

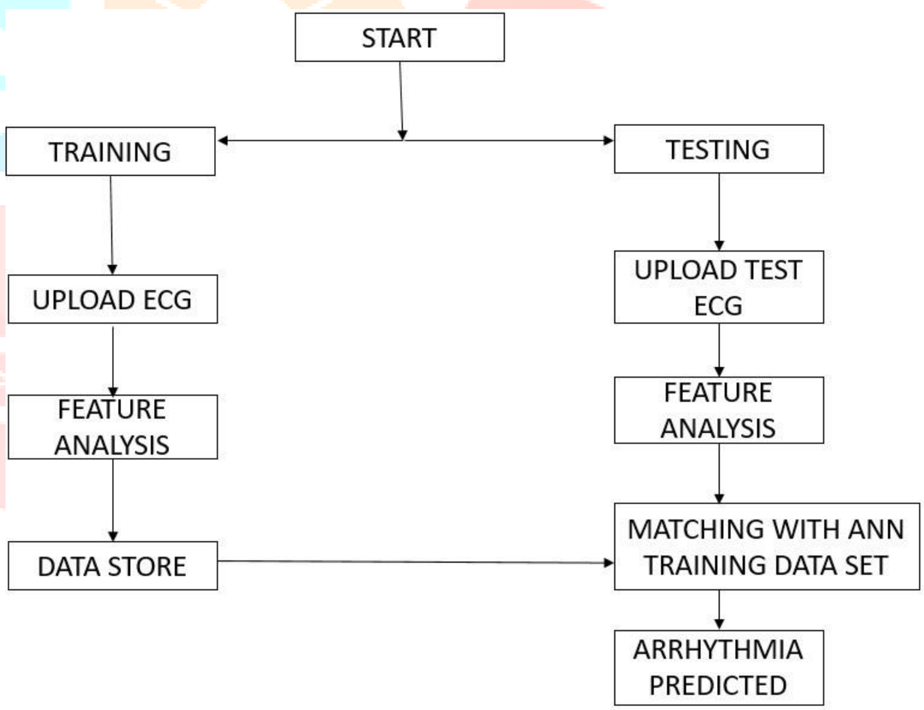

Figure 3: Block diagram of Artificial Neural Network

a model of a real system. This is used by a computer program MATLAB to create the desired results. Data is inputted and trained by this neural network and then some of the data is used for validation and actual testing. For the data in this project, 48 data samples of an ECG beat are used to train the data, 15 are used for validation, and 10 are used for testing the network on accuracy. Typically, one uses about 15% of the data to train, 15% to validate, and 70% to test the dataset. These are the default percentages suggested in MATLAB. These percentages can be manipulated based on the user, but these default percentages were not able to choose because enough data for each category is not available totest the network[8].

OUTPUTS

Input ECG signal

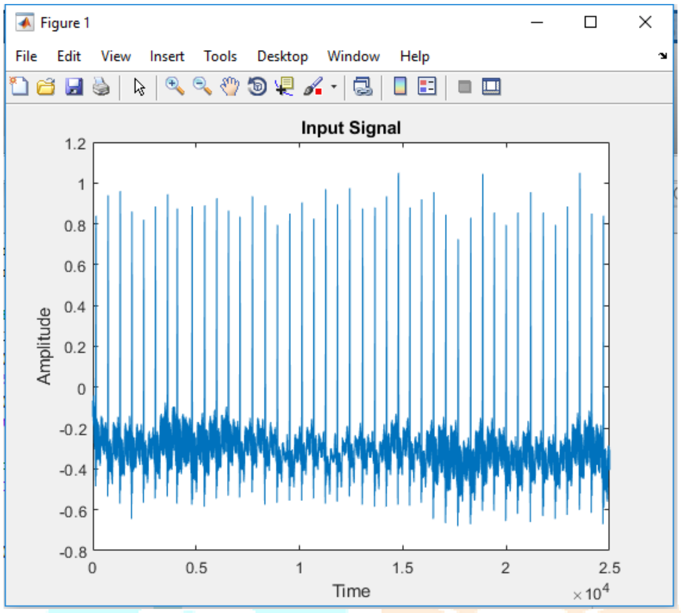

Figure 4: Noisy ECG signal

Denoised ECG signal

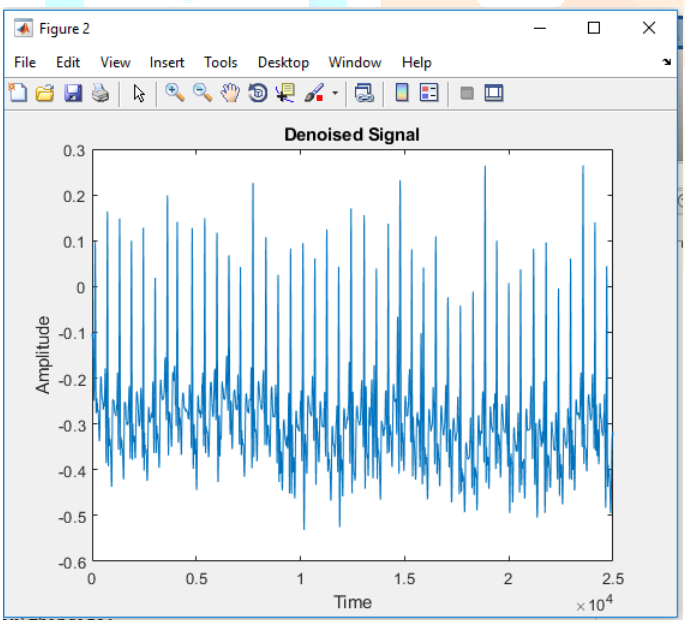

Figure 5: Noiseless ECG signal

Normal Output

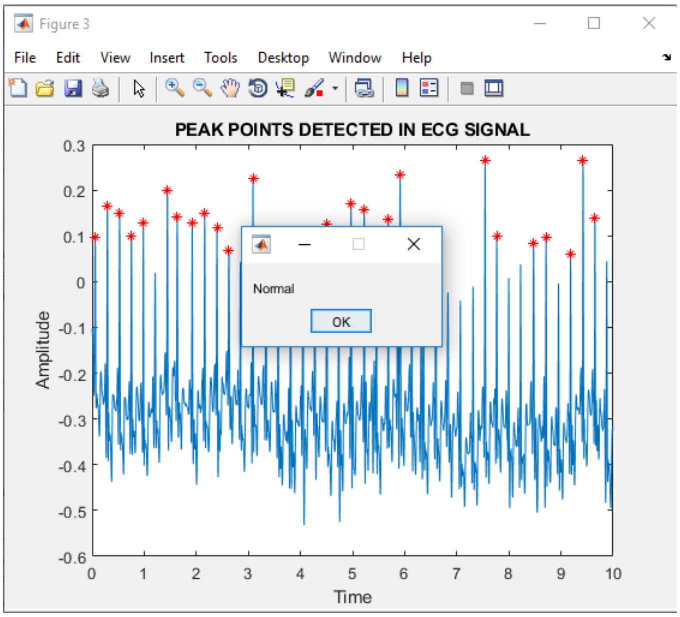

Figure 6: Normal

Premature Ventricular Contraction Output

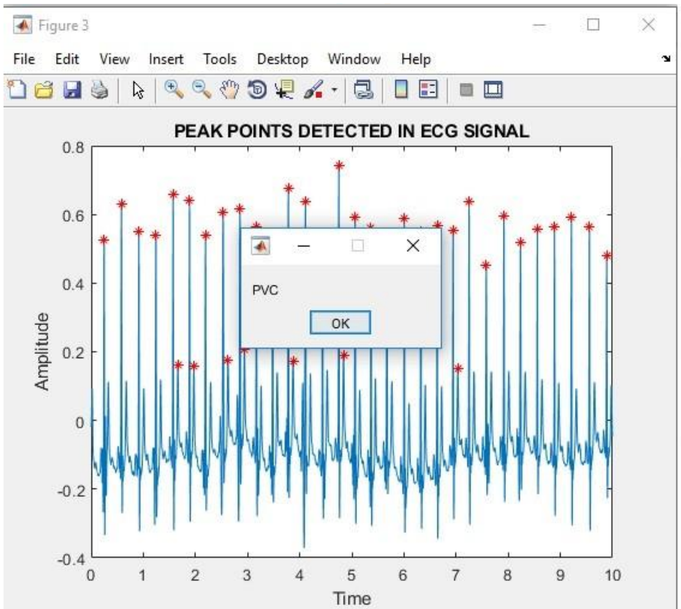

Figure 7: PVC

Paced Beats Output

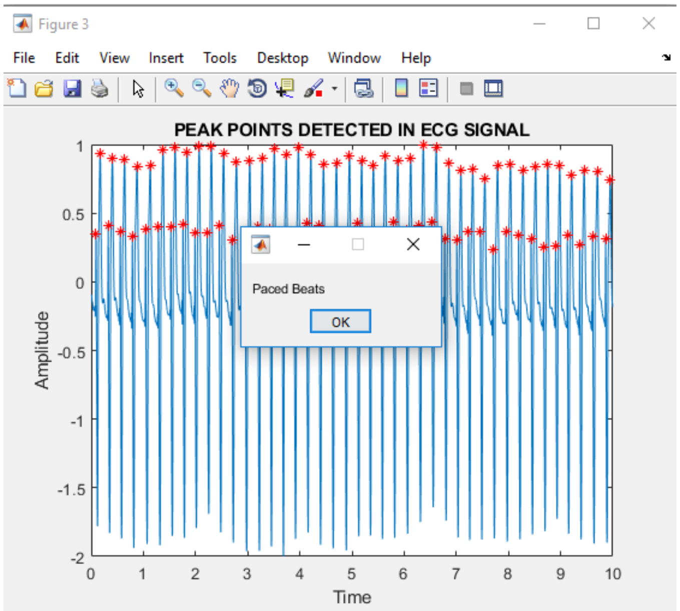

Figure 8: Paced

Left Bundle Branch Block Output

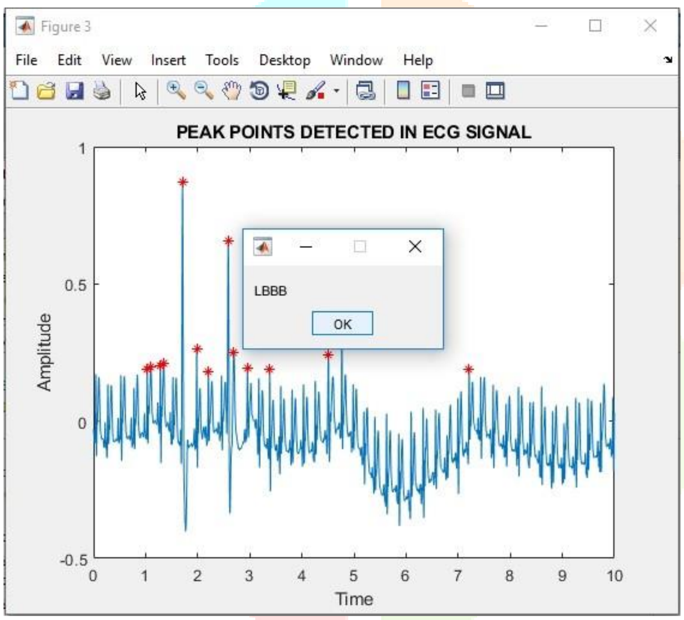

Figure 9: LBBB

Right Bundle Branch Block Output

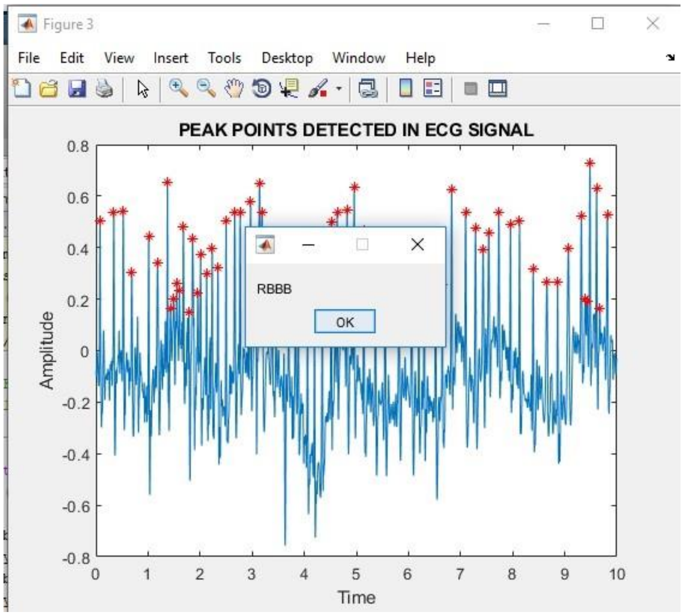

Figure 10: RBBB

Artificial Neural Network Regression Out-put

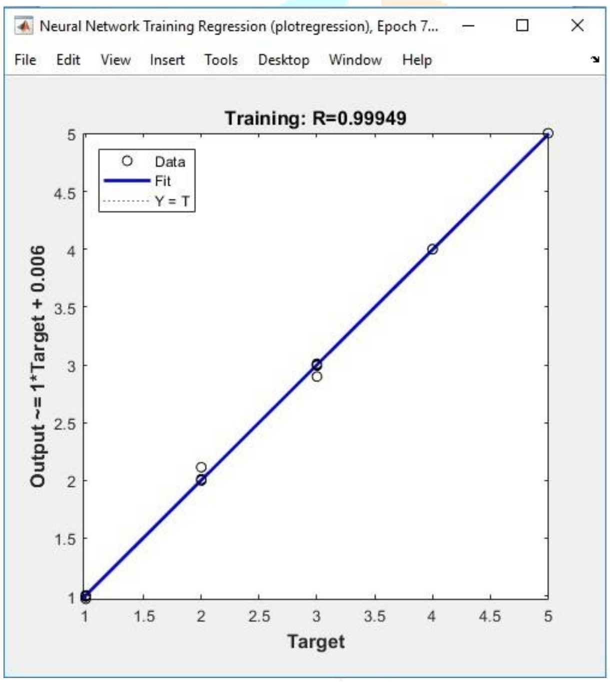

Figure 11: Regression

CONCLUSION

Here an attempt is made to help the doctor in diagnosing arrhythmia by inspecting the ECG signals. Arrhythmia detection is a very difficult task as it can also happen because of problems in other organs and mental conditions of patients. Here I am considering only ECG signals obtained from MIT-BIH database. So accuracy of prediction depends on available ECG signals and achieved reasonable accuracy.

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