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Research Paper

DETECTION OF NORMAL ECG AND ARRHYTHMIA USING ARTIFICIAL NEURAL NETWORK SYSTEM

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At the present we have various intelligent computing tools such as Artificial Neural Network (ANN) approaches are proving to be skilful when applied to a range of problems. In this paper we applied the ANN tool for detecting the normal and abnormal signal. Here the designed ANN model contained approaches the neural network adaptive potential approach and Cascade feed-forward backpropagation method is used as an optimization method. The Electrocardiogram (ECG) dynamic and nonlinear signal characteristic requires an accurate and precise detection and recognition system. This paper describes the detection of a MIT-BHI normal sinus ECG database signal and MIT-BHI Supraventricular ECG database signal based on ANN approach. Some conclusions regarding the classification of the ECG signals is obtained through analysis of the ANN. The proposed ANN modal gives the 100% accuracy for normal ECG detection and 96.65 % accuracy for abnormal ECG detection. Classification accuracies and the results created by the ANN confirmed that the proposed ANN model is very efficient in classifying the normal and abnormal ECG signals in our research, we have taken 10 s to complete ECG including many ECG bits are taken for analysis.

Keywords: Artificial Neural Network (ANN), Electrocardiogram (ECG), Fuzzy logic, MIT-BHI database

INTRODUCTION

Cardiac problems are increasing day by day. ECG is one of the most commonly used tests to diagnose the heart problem. Detection and treatment of arrhythmias have become one of the cardiac care unit's major functions. Few of the arrhythmias are Ventricular Premature Beats, a systole, Couplet, Bigeminy, Fusion beats (Shahnaz and Shaini, 2011) for getting the best result toward the unknown and unseen data the size of the training database should be at least as large as the number of modifiable parameters in ANN.

The literature in this topic reports several approaches to

Classification, including Bayesian (Willems, 2007) and heuristic approaches (Talmon, 1983),

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expert systems (Gallin, 1984), and Markov models (Coast, 1990). In general, past approaches, according to published results, seem to suffer from common drawbacks that depend on high sensitivity to noise and unreliability in dealing with new or ambiguous patterns.

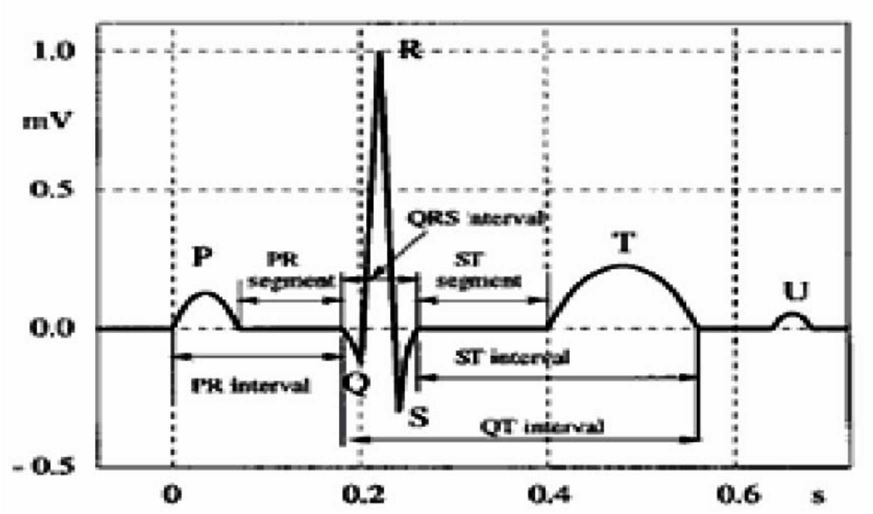
Artificial Neural Networks (ANN's) have often been proposed as tools for realizing classifiers that are able to deal even with nonlinear discrimination between classes and to accept incomplete or ambiguous input patterns. Recently, the connectionist approach has also been applied to ECG analysis with promising results (Stamkopulous, 1992; Frenster, 1990).

Electrocardiogram (ECG) represents the electrical activity of the heart. When the ECG is abnormal, it is called arrhythmia. Millions of ECGs are taken for the diagnosis of various classes of patients, where ECG can provide a lot of information regarding the abnormality in the concerned patient are analyzed by the physicians and interpreted depending upon their experience. The interpretation may vary by physician to physician.

Hence this work is all about the automation and consistency in the analysis of the ECG signals so that they must be diagnosed and interpreted accurately irrespective of the physicians. Talmon (1983) the recorded ECG waveform which is made of distinct electrical depolarization and repolarization patterns of the heart. Any disorder of heart rate or rhythm, or change in the morphological pattern, is an indication of an arrhythmia, which could be detected by analysis of the recorded ECG waveform.

A typical cycle of an ECG is shown in Figure 1. Physicians first locate such fiduciary points as Q points, R points, and S points in the ECG from which they locate the P-complexes, QRS-waves, T-complexes, and U-waves in the ECG. These waves and complexes are defined in Figure 1. Physicians then interpret the shapes of those waves and complexes. They calculate parameters to determine whether the ECG shows signs of cardiac disease or not. The parameters are the height and the interval of each wave, such as RR interval, PP interval, QT interval, and ST

Figure 1: The ECG Signal and its Different Components



segment (Figure 1) (Yukinori, 1995)

In this paper we applied normal sinus ECG database and Supraventricular Arrhythmia database, the normal sinus rhythm not only gives you an idea about the rhythm is normally generated from the sinus node and wandering in a normal manner in the heart. In most of the research paper single ECG bit taken for analysis, but in our research we have taken the 1 min complete ECG include of many ECG bit is taken for analysis which has taken a great care in case of heart beat variability. The normal value of heart bit rate depends upon age it is not same for all the normal people, normal heart rate for an infant is 150 beats in one minute maximum, even the heartbeat rate of child of five year age may 100 beats in a minute, the heart rate of adult is slower than the child, it is about 60-80 beats in one minute. In normal sinus rhythm of heart p-waves are pursued after a short gap by a QRS complex followed by a T-wave of ECG the cause of Supraventricular Arrhythmia is a quick heart rhythm of the upper chambers of the heart.

In Supraventricular Arrhythmia electrical signals or the electrical potential move through the upper chambers to lower chambers of the heart. Supraventricular Arrhythmia are usually 150-250 beats per minute but it can be both slower or faster. The most common types of supraventricular tachycardia are caused by a reentry phenomenon producing accelerated heart rates. Normally, Supraventricular Arrhythmia results in symptoms such as frequent heart beating, dizziness, shortness of breath and chest discomfort.

Figure 2a: Normal Sinus 16265 Signal of MIT-BHI

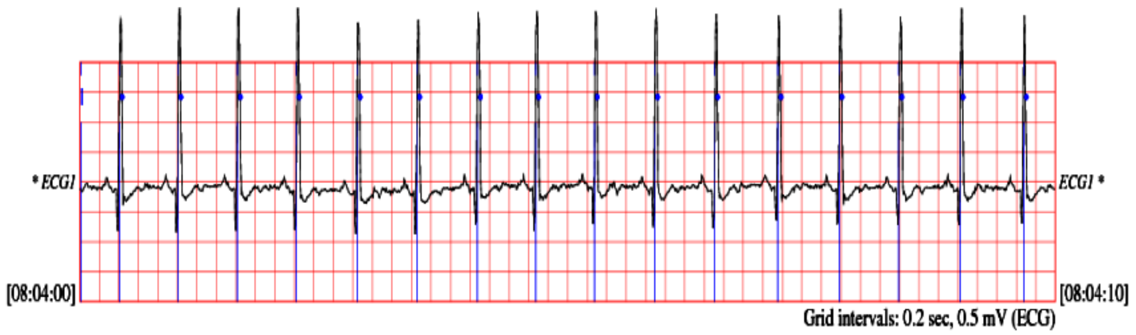


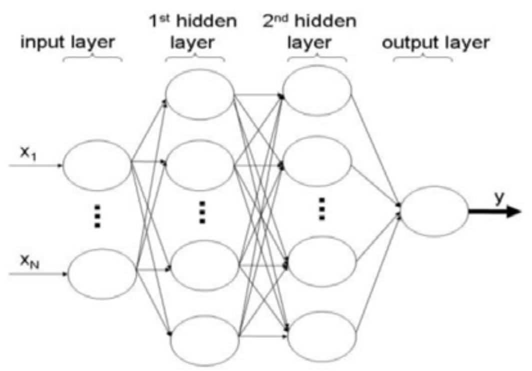
Figure 2b: Supraventricular Arrhythmia 800 signal of MIT- BHI

The image of the normal sinus rhythm database (16265) and supraventicular Arrhythmia (801) duration of 10 s and 128 Hz sampling rate of MIT-BHI is shown in the Figure (2a, b).(MIT-BIH).

ANN

We use a feed forward neural with hidden layers, as shown in Figure 3. All neurons were defined as sigmoid activation functions. The input layer consists of nodes for ECG measurement, and in the sequent hidden layers, the process neurons with the standard sigmoid activation functions were used.

Figure 3: Architecture of Neural Network



The neural network was trained by the back propagation algorithm with the selected ECG segment as its inputs and the weights of neurons as it outputs. The BPA is a supervised learning algorithm, in which a sum square error function is defined, and learning process aims to reduce the overall system error to a minimum.

The output units have weights $W^3_{i,j}$, and the hidden units have weights $W^3_{i,j}$ and $W^3_{i,j}$. During the training phase, each output neuron compares its computed activation y_k with its target value *dk* to determine the total square error E for the pattern with that neuron,

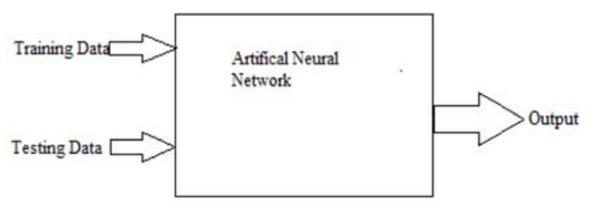
$$E = 1/2\sum_{k=1}^{m}\left(d_k - y_k\right)^2$$

where m is the number of output neurons, k represents the kth neurons. By using Backpropagation Algorithm the network has been trained with moderate values of learning rate and momentum .the weights will be terminated when the sum square error reaches a minimum values.

The weights are randomly assigned at the beginning and progressively modified backward from the output layer to the input layer to reduce overall system error, the weight update is in the direction of negative descent to maximize the speed of error reduction for effective training , it is desirable that the training data set be uniformly spread thought out the class domains, the available ECG data were used repetitively until the error converge to its minimum. Hence, an algorthim containing three steps that are (i)setting random weights; (ii) training recursion; and (iii) Detection of ECG (Kuo, 2008; Mehmet, 2010; Sadaphule *et al.,* 2012).

The block diagram of the ANN system is shown in the Figure 4, two arrows indicate the training data and testing data that applied to the cascade feed forward type ANN system. Training data used for preparing the network architecture and decide the input and output range according to the training function, number of hidden layer, the method used for optimization and training functions is used for training. After this test data is applied, on the basis

Figure 4: Artificial Neural Network System



of proposed ANN network output is determined in the form of 0 and 1 here 0 for supraventricular ECG and 1 for normal sinus ECG.

METHODOLOGY

The MIT-BIH Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. The recordings of normal sinus ECG (ECG1) database and Supraventricular ECG (ECG1) database were digitized at the rate of 128 samples per second per channel with the resolution of 11-bits over a span of 10 mV.

In our method we use 18 ECG Signal of normal sinus database, out of 18 we use 14 in training and 4 in testing. The duration of one ECG is 10 s with sampling rate 128 Hz and total sample of an ECG signal is 1280 some of the abnormal ECG is called arrhythmia in our paper we have taken supraventricular database. In abnormal database we take supraventricular arrhythmia database of 76 ECG signal out of 76 ECG signal 14 signal used for training and 62 used for testing. The sampling rate of supraventricular ECG signal is same as a normal ECG signal.

Input Data

The input database is given in the matrix from shown in the Table 1.

From the table the total 84 ECG signal is used for analysis, out of 84 28 is used for training and remaining 56 used for testing.

Training Function

Levenberg-Marquardt (trainlm):Like the quasi-Newton methods, the Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feed-forward networks), then the Hessian matrix can be approximated as

$$H = J^T J$$

and the gradient can be computed as

$$g = J^T e$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and *e* is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix.

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$X_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e$$

When the scalar *m* is zero, this is just Newton's method, using the approximate Hessian matrix. When *m* is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible. Thus, *m* is

Table 1: Training Functions

Name	Total	Training	Testing
Normal	18	14	4
ECG Database			
Supraventricular ECG database	66	14	52

decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function will always be reduced at each iteration of the algorithm (http://radio.feld.cvut.cz/matlab/toolbox/nnet/backpr11.html; and http://www.mathworks.in/help/nnet/ref/trainlm.html).

Analysis

Levenberg-Marquardt function is used for training the neural network, the description about the trainlm function is given above. The neural network object is given below:

Neural Network object:

Architecture:

numInputs: 1

numLayers: 2

biasConnect: [1; 1]

inputConnect: [1; 0]

layerConnect: [0 0; 1 0]

outputConnect: [0 1]

numOutputs: 1 (read-only)

numInputDelays: 0 (read-only)

numLayerDelays: 0 (read-only)

Sub-object structures:

inputs: {1x1 cell} of inputs

layers: {2x1 cell} of layers

outputs: {1x2 cell} containing 1 output

biases: {2x1 cell} containing 2 biases

inputWeights: {2x1 cell} containing 1 input weight

layerWeights: {2x2 cell} containing 1 layer weight

Functions:

adaptFcn: 'trains'

divideFcn: 'dividerand'

gradientFcn: 'gdefaults'

initFcn: 'initlay'

performFcn: 'mse'

plotFcns: {'plotperform','plottrainstate', 'plotregression'}

trainFcn: 'trainlm'

Parameters:

adaptParam: . passes

divideParam: . trainRatio, .valRatio, .testRatio

gradientParam: (none)

initParam: (none)

Figure 5: Neural Network

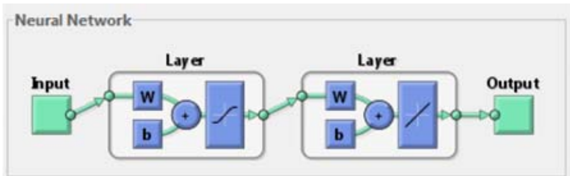
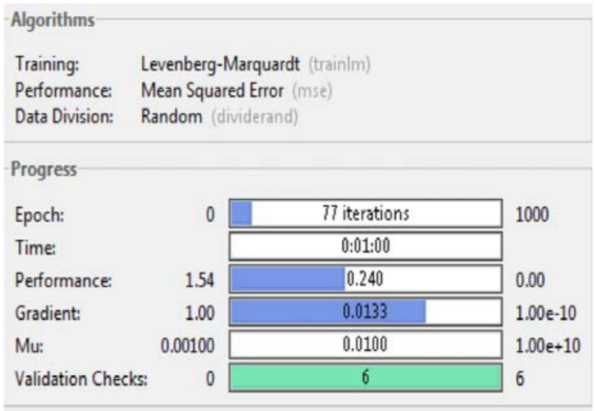


Figure 6: Algorithm and process



performParam: (none)

trainParam: .show,

.showWindow, .showCommandLine, .epochs,

.time, .goal, .max_fail, .mem_reduc,

.min_grad, .mu, .mu_dec, .mu_inc,

.mu_max

Weight and bias values:

IW: {2x1 cell} containing 1 input weight matrix

LW: {2x2 cell} containing 1 layer weight matrix

nb: {2x1 cell} containing 2 bias vectors

Figure 7: performance plot

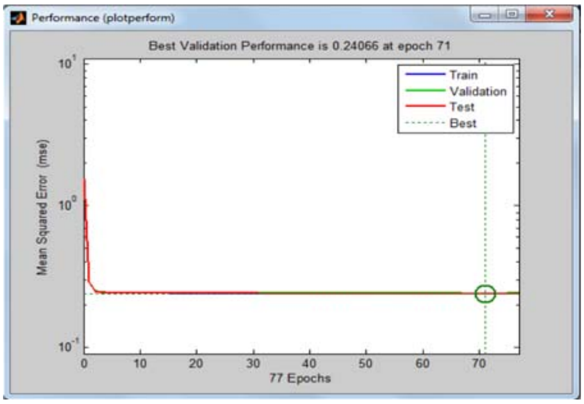


Figure 8: Training state

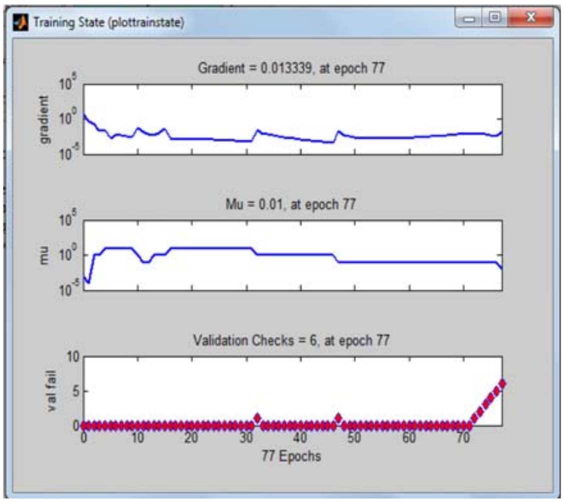


Figure 9a: Regression Plot

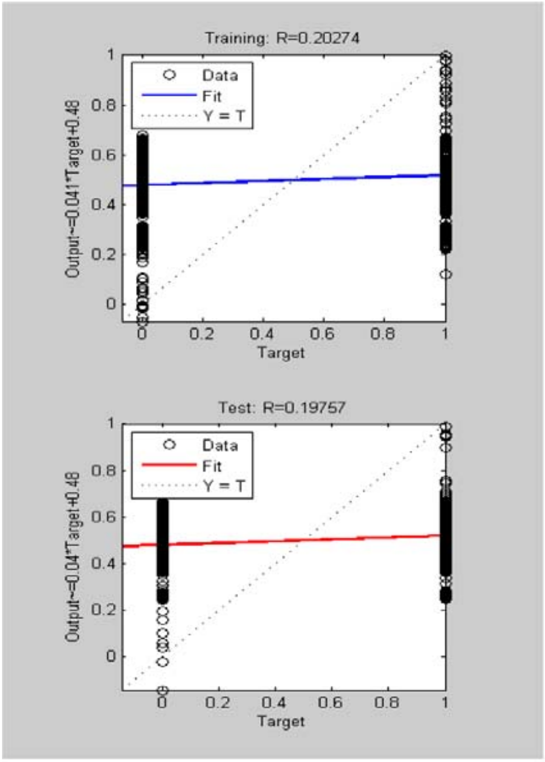
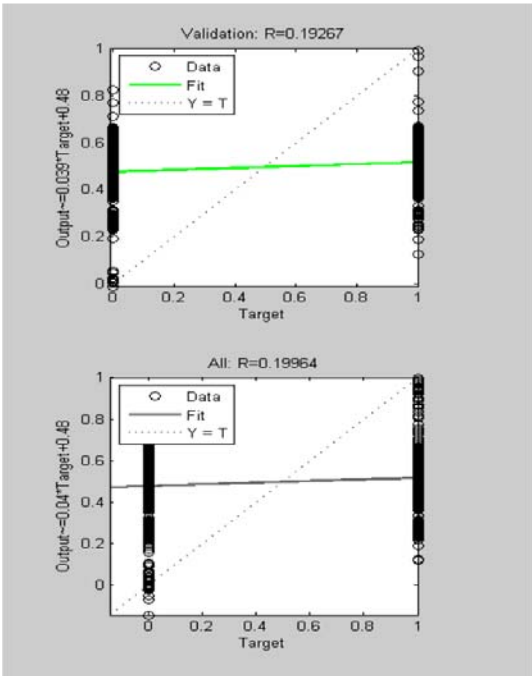


Figure 9b: Regression Plot



The proposed neural network diagram, algorithm and process diagram is given below:

The given neural network has two hidden layer between the input layer and output layer.

Table 2: Performance Result

Name	Testing signal number	Testing Result	Overall Test Accuracy
Normal sinus database	19093	Verified	100%
	16265	Verified	
	19539	Verified	
	19830	Verified	
Supraventricular Arrhythmia database	822	Verified	92.308%
	823	Verified	
	825	Verified	
	826	Verified	
	828	Verified	
	829	Verified	
	840	Verified	
	844	Verified	
	845	Verified	
	846	Verified	
	848	Verified	
	851	Verified	
	852	Verified	
	853	Verified	
	854	Verified	
	855	Verified	
	856	Verified	
	857	Verified	
Supraventricular Arrhythmia database	858	Verified	92.308%
	859	Verified	
	860	Verified	
	861	Verified	
	862	Verified	
	863	Verified	

Table 2 (Cont.)

Name	Testing signal number	Testing Result	Overall Test Accuracy
	864	Verified	
	867	Verified	
	868	Verified	
	869	Verified	
	870	Not Verified	
	871	Verified	
	872	Verified	
	873	Not Verified	
	874	Verified	
	875	Verified	
	876	Verified	
	877	Verified	
	878	Verified	
	879	Verified	
	880	Verified	
	881	Verified	
	882	Verified	
	883	Verified	
	884	Verified	
	885	Verified	
	886	Not Verified	
	887	Verified	
	888	Verified	
	889	Verified	
	890	Not Verified	
	891	Verified	
	892	Verified	
	893	Verified	

The performance graph of the neural network Is plot between the mean square error and the epoch. Here the blue line stand for training data , green for the validation and red line for the test data. performance graph, training state graph and the regression diagram is given below:

The coding Artificial Neural Network is done with the help of book *MATLAB*, “An Introduction with Applications” written by Amos Gilat on MATLAB 7.10.0 (2010a) software.(Amos, 2005)

RESULT

Result of processing of normal and abnormal ECG signal is shown in tabular form

CONCLUSION

The conclusion resulting from this work is that, by using MATLAB based the Artificial Neural Network system design and simulation (MATLAB). Some better networks can be prepared which have the capability to understand all types of ECG database. In most of the research paper single ECG bits taken for analysis, but in our research we have taken the 10 s complete ECG include of many ECG bits is taken for analysis which has taken a great care in case of heart beat variability. This type of network can be very reliable as ANN provides a better and understandable set of tools so that the network parameters can be adjusted and precisely easily, such type of network can handle a large amount of database and can work easily with unseen database. The accuracy obtained by such network is comparatively good. The above ANN method for analysis of ECG signal gives 96.65 % average percentage of correct classification without using the any feature extraction techniques. Proposed ANN model used for detection normal ECG and arrhythmia is proving to be a very reliable precise method of analyzing each signal.

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