Available online at www.pelagiaresearchlibrary.com

Pelagia Research Library

Advances in Applied Science Research, 2010, 1 (2): 76-83

ISSN: 0976-8610
CODEN (USA): AASRFC

Fusion beats extraction from ECG using neural network based soft computing techniques

[1] Shahanaz Ayub, [2]J.P.Saini

[1]*Department of Electronics and Communication, BIET, Jhansi, UP, India.*
[2]*M.M.M. Engg. College, Gorakhpur, UP, India*

ABSTRACT

ECG i.e Electrocardiogram represents 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 analysed 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. Many works have been done previously but this paper presents a new concept by application of MATLAB based tools in the same weighted neural network algorithms. This will help to reduce the hardware requirements, make network more reliable and thus a hope to make it feasible.To do so various networks were designed using the MATLAB based tools and parameters. Two classes of networks were designed, but with different training algorithms, namely Perceptron and Backpropagation. They were provided training inputs from the data obtained from the standard MIT-BIH Arrhythmia database.After training different forms of networks, they were tested by providing unknown inputs as patient data and the results in the whole process from training to testing were recorded in the form of tables. There are many types of abnormalities in ECGs like Ventricular Premature Beats, asystole, Couplet, Bigeminy, Fusion beats etc. In this paper only fusion beats have been discussed and so results associated with it only has been given, though the same principle was used to make networks for analyzing normal as well as ventricular premature beats too. The results for the fusion beats were best in the case of Feed Forward network algorithm. The percentage of correct classification is 96%. The results are compared with the previous work which concludes that the Feed Forward network with backpropagation Trainbfg algorithm is best for fusion beats classification.

Keywords: Arrhythmia, Fusion Beat, MATLAB, Artificial Neural Networks, Backpropagation, Feed Forward Network, MIT-BIH arrhythmia data base.

INTRODUCTION

Today many patients are suffering from cardiac problems. Heart disease is the most common cause of death in the world. In recent years considerable work has been done to assist cardiologists with their task of diagnosing the ECG recordings.Detection and treatment of arrhythmias has become one of the cardiac care unit's major functions. More than 3 million ECGs are taken worldwide each year for the patients with different cases, right from heart rhythm anomaly to the hormonal imbalances due to organ failures. All the samples taken have one thing in common and that is, they are analysed by the experienced doctors who depending upon their knowledge predict out the problem(s) associated with the patient which is disturbing the normal morphology of the signal. If this morphological disturbance becomes somewhat complex (such as the case of fusion beats) then it is analysed by them depending upon their experience. This experience based analysis gives different interpretations and hence different treatment procedure when they are made by different persons. Hence there is a need of a system that could analyse the ECG signals properly and with a great accuracy so that there is a less chance of mistake as well as the problem is spotted in time so that an early treatment could be started.

So to achieve this objective many works have been done in this field based on image processing, Digital Signal Processing etc and prominent among them is the use of Artificial Neural Networks [1] which has given promising results to such complex problems. Neural network based analyses made were either weight based or weightless. This work is based on weighted neurons with bias adjustments but with the application of MATLAB based algorithms and neural network structure.

The excellent features of the MATLAB [2] such as wide range of tools for network structure development and adjustment according to requirements as well as tools to analyse the results, makes it a good option to solve this complex problem in a simple way, especially the case of fusion beats. In this paper the case of fusion beats is discussed so as to have an insight into the concept of identification of fusion beats using Feed forward neural networks (MATLAB based) with back propagation algorithm. The data base used in this paper to train and test the neural network, is the standard MIT-BIH arrhythmia database [3].

Objective of the work

The objective of this work is to make the analysis of fusion beats easy so that the patient could be diagnosed for the heart problems in less time as well more accurately so that the medical practitioners have primary information about the ailment and could start a treatment early. Apart from this the project has been targeted towards the rural community and so we are also considering hardware implementation of this work but in low cost and greater efficiency.The soft computing technique used is MATLAB based neural network tools to identify the fusion beats from ECG beats.

Methodology

The database provided by the MIT-BIH arrhythmia database [2] regarding different kinds of heart rhythm abnormalities for different class of patients, is the source of data used for training and testing of the neural networks. The data from the patient number 208 was preferred and taken out for different cases of heart beats. Other patient data were also taken so as to enhance the prediction capability of the trained neural network and make it more accurate.

The data taken was used to make training inputs which represented the whole ECG cycle as well as for making test inputs. The MATLAB based Perceptron and backpropagation [4] networks were developed and training parameters were fixed for certain quantities and varied for others. The network trained were analysed using the test inputs first for all unknowns which were not used for training and then for all inputs which included both training inputs and test inputs. Analysis plot tools [4,5] were also used to understand the network capability and other properties such as Mean Squared Error (MSE) value and learning capability.

Database

The MIT-BIH Arrhythmia 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 were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. Two or more cardiologists independently annotated each record; disagreements were resolved to obtain the computer-readable reference annotations for each beat (approximately 110,000 annotations in all) included with the database. For our study purpose the record chosen was the MIT-BIH patient 208. This was chosen for two reasons:

1) The patient was without any kind of medication and had sufficient bits for normal and ventricular as well as maximum number of beats for fusion analysis among all patient data available.
2) Earlier weightless neural network analyses were done by other scholars using this patient so we wanted to compare our network and its result with their one. Figure 1. shows the sample record of data of patient 208.

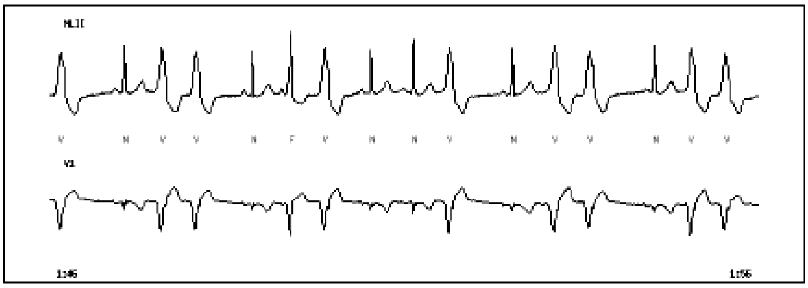

Fig. 1: A sample record of data of patient 208

From the database when the ventricular bits were derived we got the R peak values in the table form. This R peak was taken as centre and from the samples of the same patient 150 sample before this R peak value and 150 samples after it was taken to make a 301 sample input, where the ventricular bit was in the centre. Thus the input becomes a matrix of 301x1 and ready to be used in MATLAB. The same process was repeated to make all the inputs of all the kinds of inputs that are normal, fusion and ventricular.

The second condition was achieved by allowing the 151st sample to be the bit value of MLII lead signal obtained from the database for particular conditions. After the inputs were arranged in the matrix then the inputs for training were taken in two stages (not for all cases of network), named as input1 with total samples of 1809 and input2 with 2921 samples. This division was made with taking approximately 1/3rd of various kinds of samples in the first case and all the inputs fixed for training in the second case. This was done to check the chances of having desired network accuracy in minimum number of inputs.

Sample no: 2092 2093 2094. . . . . 2242 . . . . 2390 2391 2392
MLII values: 933 927 922. . . . . 1265 . . . . 992 991 990
(As input matrix)

⇧

151st bit R peak value

Fig. 2: Selection and organisation of input data

E.g. If sample number 2242 of patient 208 is a R peak then from the samples of the same patient, values for MLII lead from sample number (2242-150=)2092 to sample number(2242+150=)2392 will be input data. This is illustrated in the above Figure 2.

Hence the total inputs used were:

Table1 1: Input Matrix Structure

KIND	**INPUTS**	**MATRIX dimension**	**Training(total)**	**Testing**	**Validation**
Normal	1586	301x1586	301x1286	301x300	301x6
Fusion	734	301x734	301x584	301x150	301x6
Ventricular	992	301x992	301x792	301x200	301x6
Unclassified	259	301x259	301x179	301x80	Not applicable

Analysis

The following tables provide the results related to various beats analysed, among them the results for the fusion beats should be observed carefully.

Table 2: Backpropagation Algorithm: Feed forward Network Design Analysis Results, 'trainbfg': training algorithm

INPUTS	**HN**	TIME(in SEC)	P(cc) (%, min=97 each) UNKNOWN	P(cc) (%, min=97 each) ALL	**EPOCHS (MAX=1000)**	MSE 0.0001	RESULT
273F/2921T	5	320	98.5V,99.3N,89.33F, 97.5U	98.5V,99.2N,95.1F, 96.8U	34	0.0107	BASELINE
	10	2613	98.6V,99.9N,90.1F, 97.6U	99V,99.8N,96.1F, 97U	40	0.0111	PASSED

TRAINBFG - BGFS Quasi Newton Backpropagation training algorithm

P (CC) - Percentage of correct classifications

INPUTS- total number of samples is suffixed by T and the number above it indicates the ventricular samples in it.

HN- Hidden neurons, representing the number of neurons in the Hidden layer

MSE- Mean Squared Error; the error goal was fixed at 0.0001 and hence here the difference MSE-0.0001 is being tabulated

SUFFIXES V, N, F, AND U- in the P (cc) columns indicate respectively Ventricular, normal, fusion and unclassified beats and their percentage of correct classifications.

The following images are the analysis plots for this work where each of them interprets different properties about the network.

1). TRAINING PROCESS RESULTS

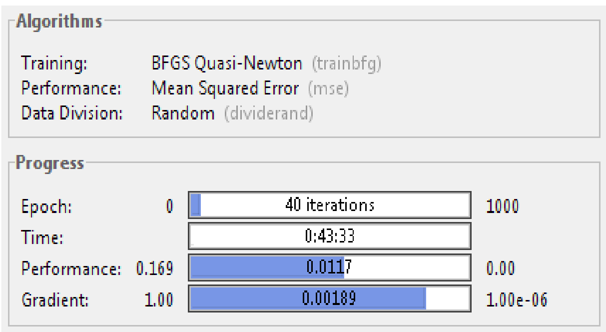

Fig. 3: Training results

Fewer epochs mean network learns in small repetitions. Less time means network achieved goal easily and shortly. Performance indicates the final MSE achieved. Lower value is associated with higher network accuracy.

2). MEAN SQUARED ERROR PLOT

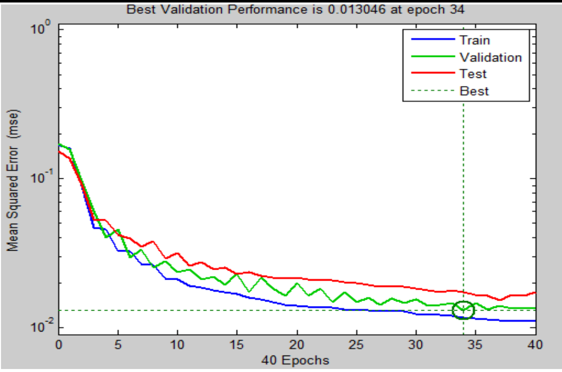

Fig. 4: Mean Squared Error Plot

Mean squared error plot shows the n achieved error value. Lower value means the less probability of false predictions.
Here network has achieved quite low error probability.

3). TRAINING STATE PLOT

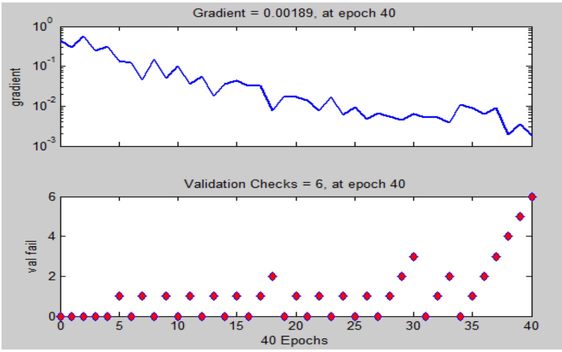

Fig. 5: Gradient and Validation Check plots

FEED-FORWARD NETWORK STRUCTURE

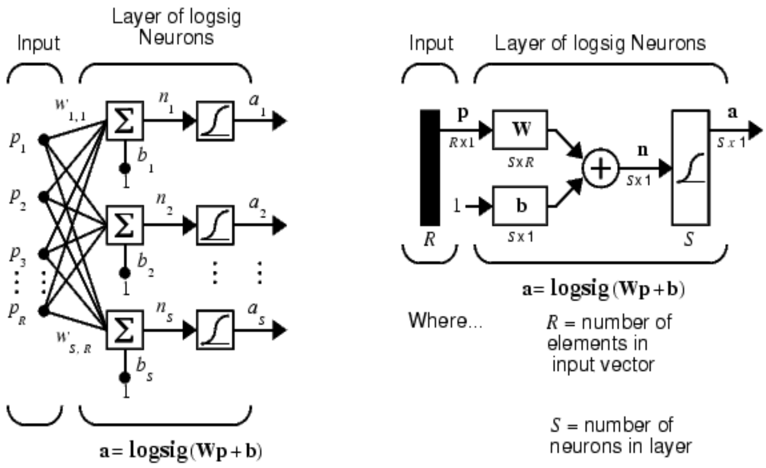

Fig. 6: Feed-Forward Network General Structure (transfer functions not same as used for analysis)

Low value of gradient plot indicates that the network is learning upto a large extent which means finer adjustments in the weights and bias. This in turn makes network more accurate and reliable, avoiding chances of false predictions.Validation plot shows the point where the network learned sufficiently and passed validation without. The point where the failures cross the defined limit is the stoppage point of training and indicates the starting of the overfitting of the data.

Inferences

- Among all cases of fusion network this network shows lowest value for MSE (0.01304) as seen in the plot. Large time for training is noticeable but due to the fact that this algorithm uses less memory, it becomes good for the case of fusion analysis.
- Gradient drop is up to 0.001 and adjustments have been made in weight up to 40 iterations after which validation error increases considerably which is the indication of over fitting of the network to the outputs. It is quite clear from the regression plot that network shows improper fitting during training but good during testing and validation.

CONCLUSION

The feed forward network based on backprapogation algorithm with trainbfg training algorithm was best for the case of fusion beats analysis because it is giving accuracy of about 96% as well as the memory requirements were also low. Hence we preferred this network for the fusion beat analysis. The results obtained with other methods like weightless neural networks, MLP [7-12] etc are compared with our results. Table three shows the comparison of the results.

Table 3 : Comparative Results with other methods

Methods	MLP	HFNS	PCA	Weightless	**Our method**
% of correct classification	80.07%	97.34%	94.39%	89.70%	**96%**
Remark	Comparatively lowest accuracy	2 ECG leads are used as inputs	Same samples are used for training& testing the network	Comparatively low accuracy	**Best Accuracy**

The conclusion derived from this work is that, by using the MATLAB based neural network design; such networks can be made which have capability to understand different class of inputs when they are fed to be analysed. Such networks can be very reliable as MATLAB provides a good set of tools so that the network parameters can be adjusted easily and precisely by just adjusting values for them and change in full length code, as was done previously, is not required. The accuracy obtained is comparatively good. The above method of analysis of ECG signal gives high percentage of correct classification.

REFERENCES

[1] Zurada, Introduction to Artificial Neural Systems, West Publishing House, **1999**.
[2] Amos Gilat, MATLAB- An Introduction with Applications, Wiley & Sons publications INC., **2005**.
[3] G.Brown, MIT-BIH Arrhythmia database,MIT, **2006**. Horward Demuth, Mark Beale, Martin Hagan, MATLAB Neural Network Toolbox, MATHWORKS INC., MATLAB Version **R2008b**, October **2008**.
[4] Horward Demuth, Mark Beale, Martin Hagan, MATLAB Simulink, MATHWORKS INC., MATLAB Version 6, October **2004**.
[5] D.M. Schreck. System and method for synthesizing leads of an Electrocardiogram US patent, 6(**2005**), 901, 285.
[6] Chickh M. A.N. Belgacem, F. Bereksi-Reguig ,Neural classifier to classify ectopic beats. Acte des IX emes rencontre de la Societe Francophone de Classification, Toulouse(**2002**), le 16-18.
[7] D.C. Thomson, J.J. Soraghan, and T.S. Durrani, An artificial neural-network based SVT/VT classification system, *Computers in Cardiology*(**1993**), pages 333-336.
[8] D.Gao, Y. Kinouchi, K. Ito, X. Zhao, Time series identification and modeling with neural network. *In. Pro. IEEE Int. Joint conference on Neural Networks*, Portland, USA(**2003**), 2454-59.
[9] D.Gao, Y. Kinouchi, K. Ito, X. Zhao, Neural Networks for Event extraction from Time Series, A back propagation Algorithm Approach, Future generation Computer System(**2003**).
[10] H.S. Chow, G.B. Moody, and R.G. Mark, Detection of ventricular ectopic beats using neural networks. *Computers in Cardiology*(**1993**), pages 659-662.
[11] J. Nadal and M.C. Bosson, Classification of cardiac arrhythmias based on principal component analysis and feedforward neural networks, *Computers m Cardiology*(**1993**), pages 341- 344.