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Using Neural and Fuzzy Software for the Classification of ECG Signals

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Abstract: Two approaches to classify the ECG biomedical signals are presented in this work. One is the Artificial Neural Network (ANN) with multilayer perceptron and the other is the Fuzzy Logic with Fuzzy Knowledge Base Controller (FKBC). Backpropagation Learning Algorithm (BPA) has been used at preset to train the ANN. MATLAB version 6.5 program was used. The ECG signals were classified to eleven groups, one of them is for the normal cases and the others represent ten different diseases. These ECG records were taken for the patients of the Surgical Specialization Center. These ECG records were divided into two groups one for training the systems and the other is for testing them. The performance of both systems, i.e. the ANN and the FL, was evaluated for different examples and Both programs give classification for all the cases. With average percentage of error between the training data group and the testing one is 4.793%. FL system takes fewer time to classify the ECG signals than the ANN because the Knowledge in the NN is automatically acquired by the BPA, but the learning process is relatively slow and the analysis of the trained network was found difficult.

Key words: Back propagation algorithm (BPA), ECG Signal, fuzzy software and neural network

INTRODUCTION

Fuzzy neural system is used to identify the dynamics of linear and nonlinear, time-invariant and time-variant, for single-input-single-output and multi-input-multi-output systems. The researcher used back propagation algorithm (BPA) to train this emulator which is utilized as a series-parallel identification model to get best results as have been mentioned by (Ajith, 1998; Al-Zohairy, 2002; Bart, 1992; Devasahayam, 2001). Joshi *et al*. (1996) proposed two new neuro-fuzzy schemes, one for classification and one for clustering problems. The classification scheme is based on simpson's fuzzy Min Max method, and relaxes some assumptions he makes. This enables our scheme to handle mutually non exclusive classes. The neuro-fuzzy clustering scheme is a multi resolution algorithm that is modeled after the mechanics of human. Peters *et al.* (1998) have studied 56-channel electroencephalograms (EEG) from three subjects whoplanned and performed three kinds of movements, left and right index finger, and right foot movement. They used autoregressive modeling of EEG time series and ANNs. They have developed a classifier that can tell which movement is performed from a segment of the EEG signal from a single trial. The high recognition rate achieved, makes the classifier suitable for a so-called "Brain -Computer Interface", a system that allows one to control a computer, or another device, with ones brain waves. Efe and Kaynak (1999) used various types of neuro-fuzzy design approaches which combine architectural (by neural network) and philosophical (by fuzzy systems) aspects of an experts resulting in an artificial brain, which can be used as an Abdul-Sada and Mahos (2002) compared the ability of a Fuzzy Neural Network and common Back-propagation network to classify x-ray gray level fracture images. Three library of x-ray image have been analyzed, first leg, second knee, third femur fractures images. The three experimental database library provided an excellent opportunity to test the ability of fuzzy neural network due to the high level of information variability often experienced with this type of images. Results were presented on the application on the three layer fuzzy networks to vision systems. They demonstrated a considerable improvement in performance by proposed fuzzy learning technique to adapt the learning rate and momentum coefficient. Linh *et al.* (2003) presented the neuro-fuzzy approach to the recognition and classification of heart rhythms on the basis of ECG waveforms. The important part in recognition fulfills the Hermite characterization of the QRS complexes. The Hermite coefficient serves as the features of the process. These features were applied to the fuzzy neural network for the recognition. The results of numerical experiments had confirmed very good performance of such solution.

MATERIALS AND METHODS

Implementation stage: This stage contains the implementation of both the ANN program and the FS program. Rawaa (2005) had published her work on using neural fuzzy system for classification of ECG signals. Fig. 1 shows all the requirements to design the software to fit the procedure of classification of ECG signal by

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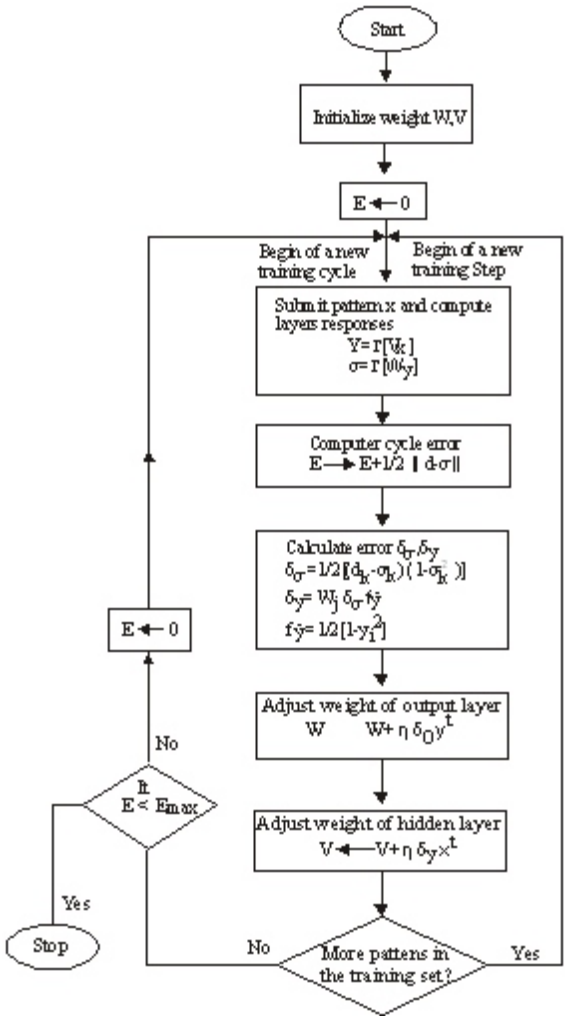

Fig 1: Flow chart Design of ECG signal

using both neural networks and fuzzy sets. Fig. 2 shows the main block diagram of the system which includes:

- collecting the data of the diseases for different patients regardless of the gender and age of the patient. - specifying the data which means dividing the data into two groups one for training the network and the other for testing it, and each one of these two groups is also divided into several groups each one represents the diagnoses of a disease.
- Processing unit which includes the processing of data by means of either ANN program or FS program.
- using the ANN program, the network is trained using the BPA using the training data group after that the classification of data is done using the testing group.
- In the FS program the data is classified using the FNBC then getting the final results.

Implementation of ANN program: This stage contains the implementation of the program. Error back

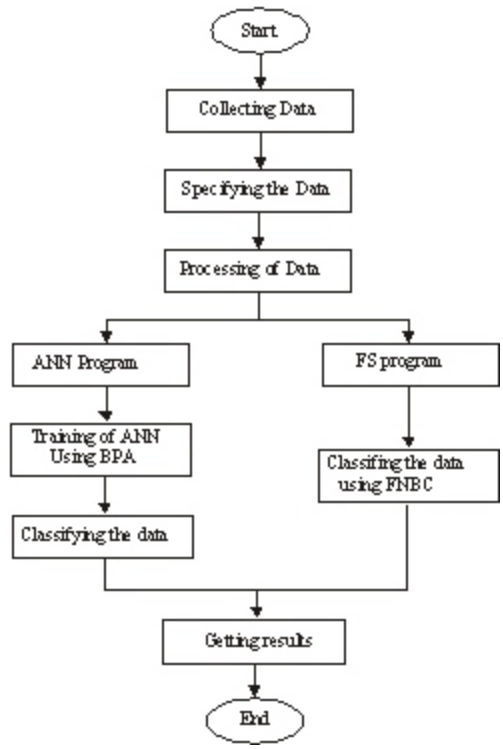

Fig 2: Flowchat of Error back propagatio n algorithm

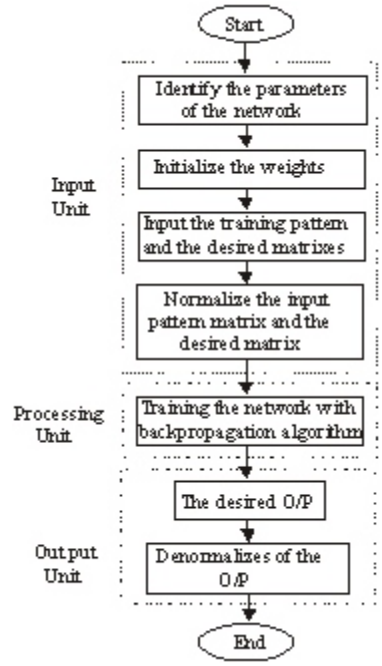

Fig 3: Black diagram of the traning process of ANN

propagation algorithm (BPA) is used to train the structure of the neural network. Fig. 3 shows the flowchart of this algorithm. The training process of the network is shown in Fig. 4. The input unit includes: identifying the parameters of the network, identifying the weights,

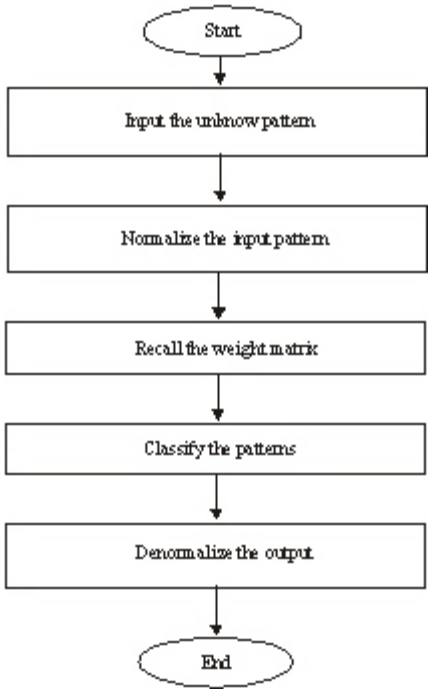

Fig 4: The block diagram of the testing process of ANN program

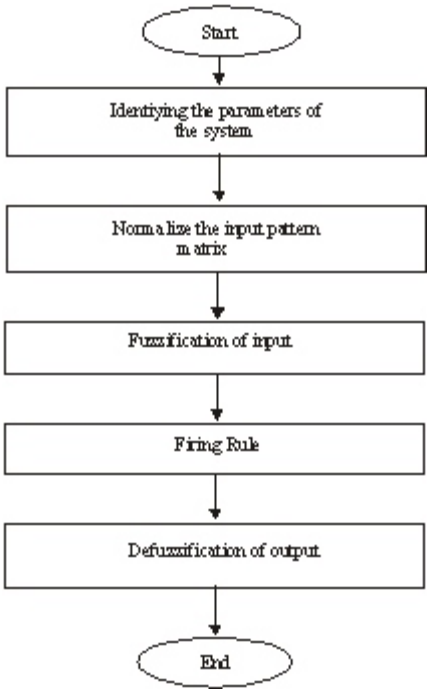

Fig 5: The computational steps of fuzzy Knowledge base Controller

entering the training patterns and the desired matrices, and normalizing the input and the desired matrices. The processing unit contains the training of the network with the input patterns using the error BPA. The output unit

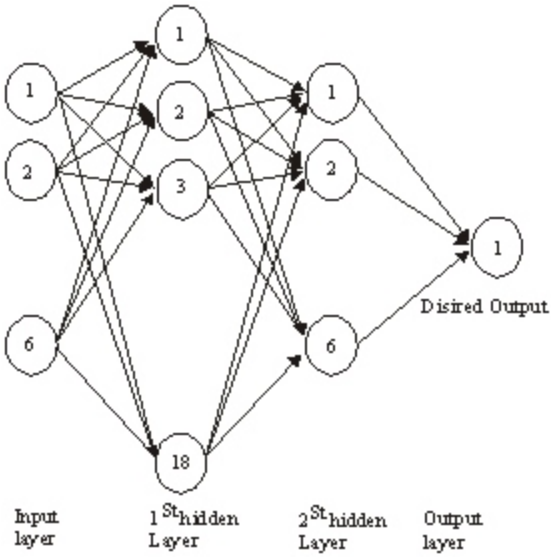

Fig 6: Neuro Fuzzy training of specifying ECG signal

gives the output of the network (the desired value) and demoralizes them. Fig. 5 shows the block diagram of the NN program. After the training of the network, the unknown patterns will be inserted in the program. The network will recognize the pattern and give the required classification.

Implementation of FS program: The block diagram of the FS is shown in Fig. 6. Identifying the parameters of the system is done by inserting the cases into a matrix as shown in Table 1. The normalization of the input pattern matrix is done by dividing the inputs on a constant value. In the fuzzification of the inputs, the identification of the membership function is produced. In the firing rule, the mathematical equation that is used in the program is chosen carefully. Because each column in the matrix represent the data of each case, therefore, the sum function for the columns is used. The defuzzification of the outputs uses the same membership function of the fuzzification. The denormalization of the outputs is the opposite of the normalization process.

QRS interval 86-216 ms QRS axis -60-51 degree P wave 5-99 ms T wave 8-219 ms RV5 0.32-2.22 ms SV1 0-2.98 ms

Tools used in this research: The neural and fuzzy classifiers used in this research are constructed, trained and simulated using the MATLAB software program (V. 6.5), which can deal with matrix in a wide horizon, since the program of this work deals with matrices. Both programs are trained and tested using a P4 personal computer with a 1.7 GHz CPU, 256 MB of RAM and 20 GB hard disk. rules to the FS program while in the ANN, each new case should be added to the inputs and the network must be trained each time a new case is added.

Table 1: Neural Network for specification

No	Item	Value
1	Pattern vector no.	10
2	Layer no.	4
3	No. of neurons in the input layer	6
4.	No. of neurons in the 1st hidden layers	18
5.	No. of neurons in the 2nd hidden layers	6
6.	No. of neurons in the output layer	1
7.	Learning rate	0.2236
8.	Momentum	0.9
9.	SSE	0.001
10.	No. Of Iterations	846

Table 2: The input vector for the structure of Fig. 6

Neuron No.	Description
1	QRS interval
2	P
3	QRSaxis
4	T
5	RV5
6	SV1

Where:
RV5: wave R in lead V5
SV1: wave S in lead V1

Present Structure of ANN and FS and Simulation result: The NN model and the FS model are built and tested for classifying ECG signals. Multilayer Perceptron model can be seen as a nonlinear system and it is trained using BPA. The results of both programs and the comparison between them are Presented.

The Architecture of neural network to classify the ECG signals: In this research the neural network structure has been built and tested to classify the ECG signals into normal and abnormal cases presenting the diagnosis of the abnormal cases, which represent the target output. This network is shown in Fig. 6, and the neural network specifications illustrated in Table 1. The input data for the two programs include normal and abnormal cases for different diseases. The input parameters of ANN are described in Table 2. It contains the parameters that affect the diagnosis of each disease. For both programs (i.e) the ANN program and the FS program, the range of data used for the training and testing for each parameter is shown below:

The problem appeared here is that the input and output vectors contain large numbers. If these vectors are inserted in their real values, the learning process will be very slow and might take very long time to finish learning. Also some of the input vectors may contain positive and negative numbers, so the (tang sigmoid) function is used because it can deal with such a problem. But, while this activation function gives an output with small decimal numbers and the desired output is of large numbers. The solution here is to normalize the input and de-normalize the output vectors. Normalization converges the values of input and desired vectors to continuous values between (-1, 1).

Table 3: The input vector of FS

parameter No.	Description
1	QRS interval
2	P
3	T
4	RV5
5	SV1

Table 4: taken by ANN and FS for the tested patterns.

Test pattern no.	ANN program	Fsprogram	Percentage of error
1	1.3750	1.2970	2.886
2	1.5620	1.1720	7.8
3	1.5000	1.1250	9.56
4	1.6410	1.0780	3.44
5	1.6320	0.9680	23.39
6	1.5450	1	35.08
7	1.5630	1.1720	3.695
8	1.6880		35.08
9	1.5460	0.9690	3.695
10	1.5150	1	3.695
11	1.6100	1.0460	0.46

The normalization equation used here is:-

$$X_{nor} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

Where: X_{nor} :normalized value,

The input parameters to the Fuzzy System: The input parameters of the FS are described in Table 3. the input vector of the FS contains five parameters. Choosing the parameters of FKBC should be done carefully so that to make the system work properly.

First of all, when choosing the normalization factor, the input patterns should be studied carefully. For this research, because the input values are very big and need to be within the range of (0-1). Therefore the normalization is done by dividing each value by (1000). The normalization equation used here is:

$$X_{nor} = X/A \quad (2)$$

where: X_{nor}: normalized value, A: normalization factor

For the fuzzification of inputs, the choice of the fuzzification module depends on the type of the firing rule employed in this application. It is the sigmoid function in this research. The advantage of the normalization is that the fuzzification, rule firing and defuzzification can be designed independently of the physical domain of the inputs and output. In the training process, the goal is to minimize the error between the actual and the desired outputs. The learning process of the error backpropagation is allowed to run until either the SSE is less than or equal to a predetermined value or else the maximum number of iteration is reached. chosen carefully to make the network for each test converge by taking many values of: neurons in the hidden layer, learning rate η and momentum α. If the number of neurons in the hidden layer is very small,

the network fails to learn or to perform what is required from it, which leads to the need to increase the number of neurons. In contrast, if the number of neurons in the hidden layer is very large, the network size increased and resulting in an increase of time of training the network. The value of η is important since large variation in learning rate can result in failure to converge. The momentum is another important factor that improves the rate of convergence. During the process, η and a are adjusted to bring the network out of local minima or to accelerate the convergence of the network. All the above parameters have been adjusted to the network as illustrated in Table 1, by trial and error. Fig. 4 shows the training curve for the structure of the ANN program of Fig. 6. This figure shows the curve of SSE against the number of iterations of training with BPA.

RESULTS

The results of both the ANN with MLP network and the Fussy Set (FS) are given in this section. Testing must be done for all the cases studied in this research, but the testing must not be carried out with the same data used in the training of both programs. For the two programs the same testing data were applied. The difference between the ANN and the FS programs is that the ANN program takes more time in the training of the network and to test the input patterns especially when new cases, are added. That means the training time increases with the increase of the number of cases. For the FS program, it is faster in the execution time and it is easier to built than the ANN program which is complicated because of the large number of parameters used in it which are the number of input, hidden and output neurons in addition to the momentum and learning rate. These parameters are chosen using the try and error method. In addition to that, because the ANN is a black box, the patterns cannot be recognized logically. On the other hand, in the FS, the behavior can be explained based on fuzzy rules and thus the performance can be adjusted by tuning the rules. Table 4 shows the time taken by the two programs to classify the tested vectors and the percentage error of the patterns taken to learn and test the two programs. A comparison between the two programs is shown in Table 4 and one can notice the following:

- For the ANN program, the time taken to classify the test patterns range from (1.3750) sec. to (1.6880) sec.
- For the FS program, the time taken to classify the test patterns range from (0.9680) sec. to (1.2970) sec. Another difference between the two programs is that in the future, if other cases are to be added, that will be done by adding new If-then rules to the FS program while in the ANN, each new case should be added to the inputs and the network must be trained each time a new case is added.

CONCLUSION

The following conclusions are pointed out:

- For the ANN program, Backpropagation learning algorithm is used to train a Multilayer perceptron network.For the FS program. Fuzzy Knowledge Base Controller is used.
- A comparison between the ANN and FS shows the following points:
  - Both give similar output and are qualified to solve nonlinear problems.
  - For the Neural Network, the knowledge is automatically acquired by the backpropagation algorithm, but the learning process is relatively slow and the analysis of the trained network is difficult.
  - The Neural Network is good at recognizing patterns but it is not at explaining how it reaches the decisions.
  - The Fuzzy Logic System, which can reason with imprecise information, is good at explaining the decisions but it cannot automatically acquire the rules used to make those decisions.
- The two programs are capable of classifying the ECG signals of one in which the two programs override by the training process.

Suggestions for future work: In this work, the back propagation learning algorithm has been used to

rain multilayer a neural network, for future work, one work can be developed toward classifying EEG can use other kinds of learning algorithms. This and/or EMG. This work deals with a limited number of ECG signal diagnosis. It is recommended to merge the neural network and fuzzy system to get neuro fuzzy system which gives a better performance .

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