Comparison of Parallel and Single Neural Networks in Heart Arrhythmia Detection by Using ECG Signal Analysis

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ABSTRACT

In this study, we have presented a method for detecting four common arrhythmias by using wavelet analysis along with the neural network algorithms. The method firstly includes the extraction of feature vectors with wavelet analysis. Then, the vectors will be categorized by means of the neural network into four classes. Input signals are recorded from two different leads. In addition, we have used both continuous and discrete wavelet analyses simultaneously for feature extraction. This results into increasing the accuracy of feature vectors extraction. Also, using the continuous wavelet in a specific scale can lead to better extraction of coefficients as well as more accurate data. In order to decrease the computational efforts and increase the training speed, the dimensions of the feature vectors have been reduced by substituting the wavelet coefficients with their statistical parameters. Furthermore, two approaches are introduced in classification of feature vectors. The first approach comprises four neural networks in the parallel form for detection of four classes, while the second approach makes use of one network for four classes. Numerical simulation results show that in comparison with the previous studies, the proposed methods are more accurate and faster. In addition, it is observed that the second approach has better capabilities in classification of data than the first one. On the other hand, the first approach is believed to have a good function for complicated data spaces.

1. INTRODUCTION

The most common way for studying and diagnosing cardiac dysfunctions is the Electrocardiogram (ECG) signal analysis. ECG is a record of the origin and the propagation of the electrical potential through cardiac muscles. The normal ventricular complexes (N) are provoked by the sinus node and are related with regular conduction path through the ventricles, which assures their normal narrow waveform. The existence of ectopic centers, as well as some blocked regions in the ventricles changes the path propagation of the activation front and leads to generation of QRS complexes with wide and bizarre waveforms related to premature ventricular contractions (PVC) and left and right bundle branch blocks (LBBB, RBBB). Detection of these diseases by means of the convenient medical approaches is usually not easy and not accurate. On the other hand, signal analyses based on ECG signals has a big potential in the diagnosis.

Various methods are used for heart beat disease detection. Accuracy of detection depends on three basic factors – the used heartbeat feature set, the applied classification method and the organization of the training strategy.

The literature contains information about various feature extraction rules, including wavelet transform (Al-Fahoum and Howitt, 1999), (Shahidi Zandi and Moradi, 2006), (Ghaffari and Golbayani, 2008), Fourier transform (Minami, Nakajima, and Toyoshima, 1999) Lyapanov exponents (Ubeyli and Gular, 2004)., (Casaleggio and Braiotta, 1997), independent component analysis (Sung-Nien and Kuan-To, 2007), (Wang, He, and Chen, 1997) principle component analysis (Ceylan and Ozbay, 2007) and also contains a lot of methods for classification such as neural network (Al-Nashash, 2000), (Foo, Stuart, Harvey, and Meyer-Baese, 2002) and neuro-fuzzy method (Engin and Demirag, 2003), (Engin, 2004), (Acharya, Bhat, Iyengar, Roo, and Dua, 2002) and K-th nearest neighbor (Christov, Jekova and Bortolan, 2005), (Jekova, Bortolan, and Chridstov, 2007), and mixture of experts (Hu, Palreddy and Tompkins, 1997) etc. In previous studies, selecting a powerful classifier was discussed and feature extraction stage was only a stage for reducing signal information. However, regarding to the neural network input data influence on the network performance, the feature extraction stage is very important. If the feature vector determines the signal characteristics better and effectively shows the discrimination between patient signals. Then the classifier can serve better and subsequently the diagnosis processes will be done more accurate. Jekova, *et al*. (2007) used the geometrical parameters and discriminating features while their method was performed manually. Here, in the present study, the features are extracted using both continuous and discrete wavelet transforms and in order to have all of observable characteristics of signals they are recorded with two leads. It should be pointed out that in most relevant works which use the advantage of discrete wavelet transform for feature extraction while for reducing the dimension of the feature vectors they ignore the coefficients of some stages which leads to missing part of information through the signal. The statistical parameters are used to replace the coefficients of wavelet transform and finally the neural networks were used by two different methods for classifying signals to four classes. Lastly, the results of these two different methods in signal classification are compared with together and with some previous studies. The presented approach, in comparison to the existing methods, is demonstrated to detect heart arrhythmia accurate and efficient under the study conditions in this paper.

2. MATERIAL AND METHODS

2.1 ECG Signals

This study involves 8 ECG recording from the **MIT-BIH** (the MIT university arrhythmia signal database) arrhythmia database. Each recording has 30 min duration and includes two leads, the modified limb lead II as well as one of the modified leads V1, V2, V3, V4 or V5. The sampling frequency is 360 Hz and the resolution is 200 samples per mV. The study focuses on the classification of the four largest heartbeat classes in the **MIT-BIH** arrhythmia database: (1) normal beats (N); (2) premature ventricular contraction (PVC); (3) right bundle branch block (RBBB); (4) left bundle branch block (LBBB). All the recorded data from this website are labeled and it is clear that each signal is belonged to which four above classes. In the present study, each data is made of 200 alternative samples which make a heartbeat to involve P, QRS and T waves (they are three waves which make a complete heart beat.) which will be used through the neural network.

2.2 Wavelet Transform (WT)

The ECG signals are considered as representative signals of cardiac physiology which are useful in diagnosing cardiac disorders. The most complete way for displaying this information can perform spectral analysis. WT provides very general techniques which can be applied to many tasks in signal processing. One of the most important applications of WT is its ability for computing and manipulating of data in compressed parameters which are often called features. Thus, the ECG signal, consisting of many data points, can be compressed into few parameters. These parameters characterize the behavior of the ECG signals. This feature uses a smaller number of parameters to represent the ECG signal which, particularly, is important for recognition and diagnostic purposes (Guler and Ubeyli, 2005). The continuous wavelet transform (CWT) of a continuous signal $x(t)$ is defined as:

$$CWT_x(\tau, a) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\psi^*(\frac{t-\tau}{a})dt \qquad (1)$$

where $\psi(t)$ is the mother wavelet, and a is the scale factor which can be thought as the inverse of frequency. As shown in Eq. (1), the mother wavelet $\psi(t)$ is scaled by a and shifted by τ to provide the basis of time-frequency representation of $x(t)$. Using the CWT, a time-scale (time-frequency) description of a signal, which is very useful to investigate the signal behavior in time and frequency domains simultaneously, is obtained (Shahidi Zandi and Moradi, 2006).

In discrete wavelet analysis, a multi-resolution formulation is used in wavelet analysis to decompose a signal event into finer and finer details. The procedure of multi-resolution decomposition of a signal $x[n]$ is schematically shown in Fig. 1.

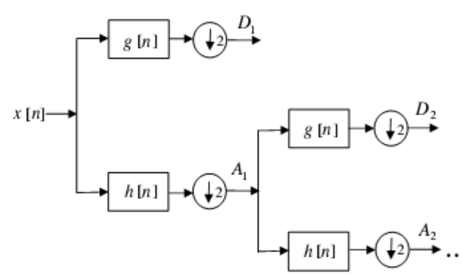

Fig. 1. Sub band decomposition of DWT implementation; $g[n]$ is the high-pass filter and $h[n]$ is the low-pass filter.

Each stage of this scheme consists of two digital filters. The first filter $g[n]$ is the discrete mother wavelet, high-pass in nature, and the second, $h[n]$ is its mirror version, with low-pass in nature. The outputs of first decomposition stage are D_1 and A_1, in which A_1 is further decomposed and this process is continued as shown in Fig. 1 (Guler and Ubeyli, 2005).

2.3 Neural Network Classifier

Artificial neural networks (ANNs) may be defined as structures comprised of densely interconnected adaptive simple processing elements (neurons) that are capable of performing massively parallel computations for data processing and knowledge representation. ANNs can be trained to recognize patterns and the nonlinear models developed during training and allow neural networks to generalize what they have previously encountered. The multilayer perceptron neural networks (MLPNNs) are the most commonly used neural network architectures since their nice features such as ability to learn and to generalize, with smaller training set requirements, faster operation, and ease of implementation. A MLPNN consists of (1) an input layer with neurons representing input variables to the problem, (2) an output layer with neurons representing the dependent variables (what are being modeled), and (3) one or more hidden layers containing neurons to help to capture the nonlinearity in the data (Guler and Ubeyli, 2005). Fig. 2 shows a general structure of the MLPNNs.

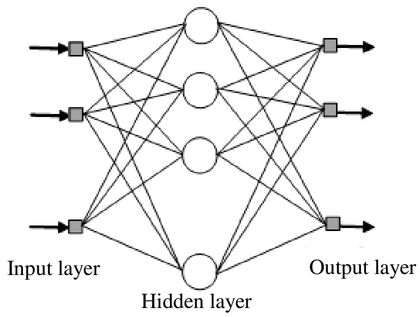

Fig. 2 The general structure of MLPNNs

3. EXPERIMANTAL RESULTS

3.1 Computation of Feature Vectors

In the present study, four various classes of ECG beats have been considered which are shown in Figs. 3(a)-(d). According to the fact that with inappropriate inputs even the best classifiers will give unacceptable results, then the selection of inputs for the neural network seems to be most important factor in designing a neural network for the patterns classification. In order to select appropriate data it should be noted that which elements of the pattern or which kind of the input data are the best description of the given data. Also it is possible that all information of a signal is not observable through a unit lead. Then, for having more information and reducing the possibility of data loss, in this study, for each heart signal two available leads from the MIT-BIH have been used. In addition, since we are eager to compare the results with each other, it is necessary to use a similar leads for all data. This matter has been considered within the records selection and all of the records have been described with two MLII and V1 leads.

Also for extraction of feature vectors, both continuous and discrete wavelet transform have been used. Continuous wavelet transform is used with Haar function and discrete wavelet is used with Daubechies function. Continuous wavelet transform with Haar function based on the Ghaffari and Golbayani (2008) can extract some information about the shape of signal and if all the wave of signals occurred or not? Also discrete wavelet with Daubechies function based on the Ceylan and Ozbay (2007) can extract some information about the sudden changes in the signal rhythm. Using these two transform simultaneously helps to extract more information from the signals.

After the wavelet transform the statistical parameters like: max, mean and standard deviation are used to compact the information of continuous and discrete wavelet coefficient more. Then feature vectors with dimension 36*1 are made.

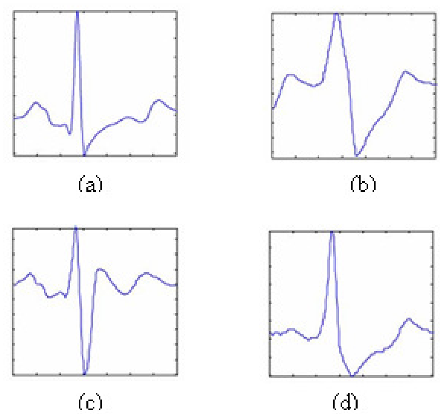

Fig. 3 (a) Normal beat (b) Premature ventricular contraction (c) Right bundle branch block (d) Left bundle branch block

3.2 Applying Neural Network on ECG Signals

In this study 110 signals are used as the test signals as shown in Table 1:

Signal Type	Number of Test Signals
N	25
PVC	25
RBBB	30
LBBB	30

Table 1- Number of test signals

These signals will classified with neural networks by two different methods. Each of these methods is explained as follows:

Method 1- Four neural networks are considered for data classification and each of these neural networks diagnoses one class of signals. For instance a neural network diagnoses normal signals and this network divides all data into two classes: 1- normal signals and 2- abnormal signals. The first network is called normal network. The second neural network is called PVC network and is dividing signals in two classes: 1-PVC signals and 2-other signals. The third network is called RBBB network and is dividing signals into two classes: 1-RBBB signals and 2-other signals. The fourth network is called LBBB network and is dividing signals into two classes as 1-LBBB signals and 2-other signals. All neural networks have three layers: input layer, hidden layer and output layer. Normal, PVC and RBBB networks have 36 neurons in input layer and 8 neurons in hidden layer and 2 neurons in output layer. LBBB network has 36 neurons in input layer and 12 neurons in hidden layer and 2 neurons in output layer.

The test results of these four neural networks are given as follows:

		Output of Normal Network	
Signal Type	**Number of test signals**	**Normal signals**	**Other signals**
Normal signals	25	25	0
Other signals	85	1	84

Table 2- Confusion[*] Matrix for Normal Network

This table shows that 25+85 signals are tested with the normal network and all of the 25 normal signals are detected as normal signal correctly and also 1 signal which is not normal is detected as a normal signal wrongly. This shows that the normal network has high separation ability in separating normal signals from the other signals.

		Output of PVC Network	
Signal Type	**Number of Test signals**	**PVC Signals**	**Other Signals**
PVC Signals	25	23	2
Other Signals	85	4	81

Table 3- Confusion Matrix for PVC Network

This table shows that 25+85 signals are tested with the PVC network and 23 of 25 PVC signals are detected as PVC signal correctly and also 4 signals which are not PVC are detected as PVC signal wrongly.

		Output of RBBB Network	
Signal Type	**Number of Test Signals**	**RBBB Signals**	**Other Signals**
RBBB Signals	30	30	0
Other Signals	80	2	78

Table 4- Confusion Matrix for RBBB Network

This table shows that 30+80 signals are tested with the RBBB network and all of the 30 RBBB signals are detected as RBBB signal correctly and also 2 signals which are not RBBB are detected wrongly. This shows that the RBBB network has high separation ability in separating RBBB signals from the other signals.

		Output of LBBB Network	
Signal Type	**Number of Test Signals**	**LBBB Signal**	**Other Signals**
LBBB Signal	30	29	1
Other Signals	80	1	79

Table 5- Confusion Matrix for LBBB Network

This table shows that 30+80 signals are tested with the LBBB network and 29 of 30 LBBB signals are detected as LBBB signal correctly and also 1 signal which is not LBBB is detected as LBBB signal wrongly.

For each network two different accuracies are determined as:

1- Specific accuracy: This shows the network accuracy in detecting the signals of its class. It is obtained for example for normal network by dividing number of signals which they detected normal to the number of tested signals which they are normal. Then for normal network this accuracy will be 100% (25/25).

2- Total accuracy: This shows the network accuracy in detecting the signals for both two classes. It is obtained by dividing the number of signals which they are detected correct to the number of total signals. For example for normal network it will be 99%.

[*] Confusion matrix is a visualization tool typically used in supervised learning . Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class.

Table 6 shows these two accuracies for each neural network:

Network	Specific Accuracy (%)	Total Accuracy (%)
Normal	100	99
PVC	92	94.5
RBBB	100	98.2
LBBB	96.7	98.2

Table 6- Neural Network Accuracies

The other important issue is the network ability in data separation. Network separation ability for example about normal network is to determine how many signals of PVC, RBBB, LBBB signals are correctly detected and assigned to abnormal signal class. For calculating this item, the number of signals which detected will bring by more details in the table below:

Network	Number of Signals			
	Normal	**PVC**	**RBBB**	**LBBB**
Normal	----------	24	30	30
PVC	23	----------	29	29
RBBB	25	23	----------	30
LBBB	25	24	30	---------

Table 7- Number of Signals which correctly detected

The separation abilities for the networks are in the table below:

Network	Signal Class			
	Normal	**PVC**	**RBBB**	**LBBB**
Normal	----------	96%	100%	100%
PVC	92%	----------	96.7%	96.7%
RBBB	100%	92%	----------	100%
LBBB	100%	96%	100%	---------

Table 8 - Result of Network Separation Ability

From the recorded results in the above table it can be seen that the accuracy of the normal network in separating PVC signals from normal signals is 96%. It means that 24 signals of 25 signals of PVC class are correctly assigned to abnormal signal class. Also the accuracy for separating RBBB and LBBB signals from normal signals is 100%.

By using neural network in parallel form, after training of 4 networks the test vectors are fed to all four networks and the class of each test signal is determined by these four outputs. It can often happen that a signal will be detected by two networks. For final classification a logical decision must be helpful to detect a correct class for signal. In this study three methods for this logical decision are explained as below:

A- If a signal is only detected by a network, this signal is belonging to the class of this network. If a signal is detected by two or three networks simultaneously, this signal is considered as an unclassified signal. Therefore, in this method the signals are either detected correctly or wrongly, or remained unclassified.

B- In this method, the class of a signal is determined according to the more accurate network's detection. For example if a signal is detected by two normal network and PVC network, by considering that the specific accuracy of normal network is 100% and this accuracy for PVC network is 92% then it will be concluded that the signal is normal.

C- This method is based on separation ability of the neural networks. On the other hand, if a signal is detected by two networks simultaneously, the signal is assigned to the class of network with higher separating ability. For example if a signal is detected by two normal and PVC networks, this signal is assigned to normal signal class. This detection is because of difference between the separation ability of normal neural network in separating normal signals from PVC signals (96%) and this ability for PVC network (92%).

As the above explanations it is clearly seen that this method of classification leads to reduction in classification error. We are using the neural networks in the parallel form. It means that each signal is fed to all networks for class detection. Then, the networks can cover their weaknesses and therefore the final result will be more accurate. The results of implementation of these three logical decisions on four network outputs are as follows:

Signal Classes	Detected Class				
	Normal	**PVC**	**RBBB**	**LBBB**	**Unclassified**
Normal	24	------	--------	--------	1
PVC	1	21	1	--------	2
RBBB	---------	------	29	--------	1
LBBB	---------	1	---------	29	--------

Table 9- Confusion Matrix for result of Method A

Signal Classes	Detected Class			
	Normal	**PVC**	**RBBB**	**LBBB**
Normal	25	---------	--------	--------
PVC	1	21	2	1
RBBB	---------	---------	30	--------
LBBB	---------	1	---------	29

Table 10- Confusion Matrix for result of Method B

Signal Classes	Detected Class			
	Normal	PVC	RBBB	LBBB
Normal	25	---------	--------	--------
PVC	1	23	1	--------
RBBB	---------	1	29	--------
LBBB	---------	1	---------	29

Table 11- Confusion Matrix for result of Method C

For evaluating the classification methods some statistical parameters are defined as follows:

1- Specificity (Sp_i) $= \dfrac{TN_i}{TN_i + FP_i}$

2- Sensitivity (Se_i) = $\dfrac{TP_i}{TP_i + FN_i}$

where TP_i (true positive) is the number of heartbeats of the ith class, which are correctly classified, TN_i (true negative) is the number of heartbeats which is not belonging to and classified in the ith class, FP_i (false positive) is the number of heartbeats classified erroneously in the ith class and finally FN_i (false negative) is the number of heartbeats of ith class which is classified in a different class. These statistical parameters for three methods are showed in the Tables 12-14 below:

Network	Sp_i %	Se_i %
Normal	98.8	96
PVC	98.8	84
RBBB	98.8	96.7
LBBB	100	96.7

Table 12- The Result of Method A

Network	Sp_i %	Se_i %
Normal	98.8	100
PVC	98.8	84
RBBB	97.5	100
LBBB	98.8	96.7

Table 13- The Result of Method B

Network	Sp_i %	Se_i %
Normal	98.8	100
PVC	97.6	92
RBBB	98.8	96.7
LBBB	100	96.7

Table 14- The Result of Method C

In Tables 15-16, comparison results of three methods in terms of specificity and sensitivity are presented. As shown in Table 15, all of these three methods have same specificity ability for normal signal. Methods A and B have better results for PVC signals and also methods A and C have better results for RBBB and LBBB signals. Overall, method A shows the best results.

Signal Type	Sp_i (%)		
	Method A	Method B	Method C
Normal	98.8	98.8	98.8
PVC	98.8	98.8	97.6
RBBB	98.8	97.5	98.8
LBBB	100	98.8	100

Table 15- Comparison Three Methods in Specificity Factor

The sensitivity of three methods is compared in Table 16 below:

Signal Type	Se_i (%)		
	Method A	Method B	Method C
Normal	96	100	100
PVC	84	84	92
RBBB	96.7	100	96.7
LBBB	96.7	96.7	96.7

Table 16- Comparison Three Methods in Sensitivity Factor

In summary with considering these given parameters and accuracy parameter, it can be concluded that method C provides the best performance based on the separating ability.

Method 2- For classifying data in four classes by neural network, a MLPNNs with three layers is considered, having 36 neurons in input layer, 12 neurons in hidden layer and 4 neurons in output layer. The outputs of neural network for four classes are assigned to four target vectors as follows: normal signal (1,0, 0, 0) , premature ventricular contraction (0,1,0,0) , right bundle branch block (0,0,1,0) and left bundle branch block (0,0,0,1). The training method of neural network is chosen to be back propagation error. For increasing the learning speed the Levenberg-Marquradt method has been used. The results of neural network training are described in Confusion matrix as below.

Signal type	Number of signal	Neural network output			
		N	*PVC*	*RBBB*	*LBBB*
N	25	25	0	0	0
PVC	25	1	24	0	0
RBBB	30	0	0	30	0
LBBB	30	0	1	0	29

Table 17- Confusion Matrix

According to the Confusion matrix it is observed that all of the normal signals and the right bundle branch block signals are diagnosed correctly but one of the signals between premature ventricular contractions is diagnosed incorrectly and is assigned to normal signals class. In addition, one of right bundle branch signals is also diagnosed incorrectly and assigned to be in premature ventricular contraction class.

The statistical parameters are computed for 4 classes and are listed in Table 18.

Signal type	Sp_i (%)	Se_i (%)
N	98.8	100
PVC	98.8	96
RBBB	100	100
LBBB	100	96.7

Table 18- Statistical Parameter Value of Neural Network Performance

4. DISCUSSION AND CONCLUSION

In this paper, wavelet transform and neural network are used for heart arrhythmia signal classification. Selected signals are belonging to four different classes and signals are recorded from two leads (MLII & V1). Wavelet transform is used for feature extraction and then feature vectors are classified by two different methods by using neural networks. The key results of these two methods are compared in Tables 19 and 20.

Signal Type	Se_i (%)			
	Method 1			Method 2
	Method A	Method B	Method C	
Normal	96	100	100	100
PVC	84	84	92	96
RBBB	96.7	100	96.7	100
LBBB	96.7	96.7	96.7	96.7

Table 19- Methods Comparison in Sensitivity

Signal Type	Sp_i (%)			
	Method 1			Method 2
	Method A	Method B	Method C	
Normal	98.8	98.8	98.8	98.8
PVC	98.8	98.8	97.6	98.8
RBBB	98.8	97.5	98.8	100
LBBB	100	98.8	100	100

Table 20- Methods Comparison in Specificity

According to Tables 19 and 20 the results of second method is better than first method which has three shapes. Therefore the second method of signal classification, which uses a neural network for signal classification, is more accurate than first method.

The key results of the second method are compared with previous study in Table 21.

	This study(Method2)	**Sung-Nien [9]**
	WT-BPNN method	***ICA-PNN method***
Signal type	Sp_i (%)	Sp_i (%)
N	98.8	99.9
PVC	98.8	98
RBBB	100	99.97
LBBB	100	99.65

Table 21- comparison of the second method results with the pervious study

According to Table 21 the results of the second method are much better than the previous study Sung-Nien and Kuan-To (2007) in three types of signals: premature ventricular contraction, right bundle branch block and left bundle branch block. According to the same method for classification in two studies the difference between their results is because of different feature extraction methods. Therefore the feature extraction method that is used in this study is a better method to determine signal characteristics.

The results of the second method are compared with the Ceylen and Ozbay (2007) study in Table 22. In their study such as second method of this study, wavelet is used feature extraction and neural network is used for classification. It is clearly to see that the second method of this study serves more effectively than the previous one. The use of statistical indices of wavelet coefficients in second method of this study provides considerable increase in training speed and the accuracy of diagnosis.

	This Study(Method2)	Ceylen-Ozbay's Study
Test error	0.158	0.4
CPU time (s)	10	85.44

Table 22- Comparison of second method with pervious study

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