Expert Systems with Applications 27 (2004) 323–330

Expert Systems with Applications

www.elsevier.com/locate/eswa

Application of adaptive neuro-fuzzy inference system for detection of electrocardiographic changes in patients with partial epilepsy using feature extraction

İnan Güler*, Elif Derya Übeyli

Department of Electronics and Computer Education, Faculty of Technical Education, Gazi University, Teknikokullar, Ankara 06500, Turkey

Abstract

In this study, a new approach based on adaptive neuro-fuzzy inference system (ANFIS) was presented for detection of electrocardiographic changes in patients with partial epilepsy. Decision making was performed in two stages: feature extraction using the wavelet transform (WT) and the ANFIS trained with the backpropagation gradient descent method in combination with the least squares method. Two types of electrocardiogram (ECG) beats (normal and partial epilepsy) were obtained from the MIT-BIH database. The proposed ANFIS model combined the neural network adaptive capabilities and the fuzzy logic qualitative approach. Some conclusions concerning the impacts of features on the detection of electrocardiographic changes were obtained through analysis of the ANFIS. The performance of the ANFIS classifier was evaluated in terms of training performance and classification accuracies and the results confirmed that the proposed ANFIS classifier has potential in detecting the electrocardiographic changes in patients with partial epilepsy.

Keywords: Adaptive neuro-fuzzy inference system (ANFIS); Fuzzy logic; Wavelet transform; Electrocardiographic changes; Partial epilepsy

1. Introduction

The electrocardiogram (ECG) signal is the recording of the bioelectrical and biomechanical activities of the cardiac system. It provides valuable information about the functional aspects of the heart and cardiovascular system (Foo, Stuart, Harvey, & Meyer-Baese, 2002; Maglaveras, Stamkopoulos, Diamantaras, Pappas, & Strintzis, 1998; Saxena, Kumar, & Hamde, 2002). Epileptic seizures are associated with several changes in autonomic functions, which may lead to cardiovascular, respiratory, gastrointestinal, cutaneous, and urinary manifestations. Cardiovascular changes have received the most attention, because of their possible contribution to sudden unexplained death in epilepsy patients. The ECG should be reviewed for high risk cardiac abnormalities during epileptic seizures. A change in heart rate can be used as an extra clinical sign and can be very informative with respect to the first manifestation of the epileptic discharge (Leutmezer, Schernthaner, Lurger, Pötzelberger, & Baumgartner, 2003; Opherk, Coromilas, & Hirsch, 2002; Rocamora, Kurthen, Lickfett, von Oertzen, & Elger, 2003; Tomson, Ericson, Ihrman, & Lindblad, 1998; Zijlmans, Flanagan, & Gotman, 2002).

Conventional methods of monitoring and diagnosing electrocardiographic changes rely on detecting the presence of particular signal features by a human observer. Due to large number of patients in intensive care units and the need for continuous observation of such conditions, several techniques for automated electrocardiographic changes have been developed in the past 10 years to attempt to solve this problem. Such techniques work by transforming the mostly qualitative diagnostic criteria into a more objective quantitative signal feature classification problem. The techniques have been used to address this problem such as the analysis of ECG signals for detection of electrocardiographic changes using the autocorrelation function, frequency domain features, time frequency analysis, and wavelet transform (WT) (Addison et al., 2000; Dokur & Ölmez, 2001; Foo et al., 2002; Kundu, Nasipuri, & Basu, 2000; Maglaveras et al., 1998; Nugent, Webb, Black, Wright, & McIntrye, 1999; Saxena et al., 2002; Simon & Eswaran, 1997; Sternickel, 2002). The results of the studies in the literature have demonstrated that the WT is the most promising method to extract features from the ECG signals (Addison et al., 2000;

* Corresponding author. Tel.: +90-312-212-3976; fax: +90-312-212-0059.

E-mail address: iguler@gazi.edu.tr (İ. Güler).

0957-4174/$ - see front matter © 2004 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2004.05.001

Dokur & Ölmez, 2001; Saxena et al., 2002; Sternickel, 2002). In this respect, in the present study for detection of electrocardiographic changes in patients with partial epilepsy, the WT was used for feature extraction from the ECG signals belonging to the normal and the partial epilepsy subjects.

The WT can be thought of as an extension of the classic Fourier transform, except that, instead of working on a single scale (time or frequency), it works on a multi-scale basis. This multi-scale feature of the WT allows the decomposition of a signal into a number of scales, each scale representing a particular coarseness of the signal under study. The WT provides very general techniques which can be applied to many tasks in signal processing. One very important application is the ability to compute and manipulate data in compressed parameters which are often called features (Akay, 1997; Akay & Mello, 1997; Daubechies, 1990; Zhang, Wang, Wang, & Liu, 2001). Thus, the ECG signal, consisting of many data points, can be compressed into a few parameters. These parameters characterize the behavior of the ECG signal. This feature of using a smaller number of parameters to represent the ECG signal is particularly important for recognition and diagnostic purposes (Addison et al., 2000; Dokur & Ölmez, 2001; Saxena et al., 2002; Sternickel, 2002).

Artificial neural networks (ANNs) are computational tools for pattern classification including diagnosis of diseases that have been the subject of renewed research interest during the past 15 years (Baxt, 1990; Güler & Übeyli, 2003; Miller, Blott, & Hames, 1992; Übeyli & Güler, 2003). Recent advances in the field of ANNs have made them attractive for analyzing signals. However, fuzzy set theory plays an important role in dealing with uncertainty when making decisions in medical applications. Therefore, fuzzy sets have attracted the growing attention and interest in modern information technology, production technique, decision making, pattern recognition, diagnostics, data analysis, etc. (Dubois & Prade, 1998; Kuncheva & Steimann, 1999; Nauck & Kruse, 1999). Neuro-fuzzy systems are fuzzy systems which use ANNs theory in order to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy systems harness the power of the two paradigms: fuzzy logic and ANNs, by utilising the mathematical properties of ANNs in tuning rule-based fuzzy systems that approximate the way man processes information. A specific approach in neuro-fuzzy development is the adaptive neuro-fuzzy inference system (ANFIS), which has shown significant results in modeling nonlinear functions. In ANFIS, the membership function parameters are extracted from a data set that describes the system behavior. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion (Jang, 1992, 1993). Successful implementations of ANFIS in biomedical engineering have been reported, for classification (Belal et al., 2002; Usher, Campbell, Vohra, & Cameron, 1999) and data analysis (Virant-Klun & Virant, 1999).

In this study, a new approach based on ANFIS was presented for analysis of electrocardiographic changes in patients with partial epilepsy. The ANFIS was used to detect electrocardiographic changes when wavelet coefficients defining the behavior of the ECG signal were used as inputs. The ANFIS presented in this study was trained with the backpropagation gradient descent method in combination with the least squares method. The ANFIS classifier was then trained and tested with the computed detail wavelet coefficients of ECG signals obtained from normal subjects and subjects suffering from partial epilepsy. The correct classification rates and convergence rates of the ANFIS were examined and then performance of the ANFIS was reported. Finally, some conclusions were drawn concerning the impacts of features on the detection of electrocardiographic changes in patients with partial epilepsy.

2. Materials and method

Decision making was performed in two stages: feature extraction using the WT (8 detail wavelet coefficients selected as ANFIS inputs) and classification using the ANFIS trained with the backpropagation gradient descent method in combination with the least squares method. The ECG signals from the MIT-BIH database (MIT-BIH Database, 2003) were used to train and test the proposed ANFIS. A rectangular window, which was formed by 256 discrete data, was selected so that it contained a single ECG beat. For two classes (normal and partial epilepsy) training and test sets were formed by 360 vectors (180 vectors from each class) of 8 dimensions (detail wavelet coefficients).

2.1. Feature extraction using wavelet transform

The WT decomposes a signal onto a set of basis functions called wavelets. These are obtained from a single prototype wavelet, called a mother wavelet, by dilations and contractions, as well as shifts. Wavelets may be used to decompose a signal at various resolutions; this process is referred to as multi-resolution signal decomposition. A general signal, e.g. an ECG, can be considered as a superposition of different structures occurring on different time scales at different times. One purpose of wavelet analysis is to separate and sort these underlying structures of different time scales. It is known that WT is better suited to analyze nonstationary signals, since it is well localized in time and frequency. The main advantage of the WT is that it has a varying window size, being broad at low frequencies and narrow at high frequencies, thus leading to an optimal time-frequency resolution in all frequency ranges (Akay, 1997; Akay & Mello, 1997; Daubechies, 1990; Zhang et al., 2001).

All WTs can be specified in terms of a low-pass filter h, which satisfies the standard quadrature mirror filter condition:

$$H(z)H(z^{-1}) + H(-z)H(-z^{-1}) = 1, \tag{1}$$

where $H(z)$ denotes the z-transform of the filter h. Its complementary high-pass filter can be defined as

$$G(z) = zH(-z^{-1}). \tag{2}$$

A sequence of filters with increasing length (indexed by i) can be obtained:

$$H_{i+1}(z) = H(z^{2^i})H_i(z)$$

$$G_{i+1}(z) = G(z^{2^i})H_i(z), \quad i = 0, \ldots, I-1 \tag{3}$$

with the initial condition $H_0(z) = 1$. It is expressed as a two-scale relation in time domain

$$h_{i+1}(k) = [h]_{\uparrow 2^i} \times h_i(k) \qquad g_{i+1}(k) = [g]_{\uparrow 2^i} \times h_i(k), \tag{4}$$

where the subscript $[\cdot]_{\uparrow m}$ indicates the up-sampling by a factor of m and k is the equally sampled discrete time.

The normalized wavelet and scale basis functions $\varphi_{i,l}(k)$, $\psi_{i,l}(k)$ can be defined as

$$\varphi_{i,l}(k) = 2^{i/2}h_i(k - 2^i l) \qquad \psi_{i,l}(k) = 2^{i/2}g_i(k - 2^i l), \tag{5}$$

where the factor $2^{i/2}$ is an inner product normalization, i and l are the scale and translation parameters, respectively. The discrete wavelet transform decomposition can be described as

$$s_{(i)}(l) = x(k) \times \varphi_{i,l}(k) \qquad d_{(i)}(l) = x(k) \times \psi_{i,l}(k), \tag{6}$$

where $s_{(i)}(l)$ and $d_i(l)$ are the approximation coefficients and the detail coefficients at resolution i, respectively (Akay, 1997; Akay & Mello, 1997; Daubechies, 1990; Zhang et al., 2001).

The smoothing feature of the Daubechies wavelet of order 1 made it more suitable to detect electrocardiographic changes. Therefore, the wavelet coefficients were computed using the Daubechies wavelet of order 1 in the present study. The 128 detail wavelet coefficients of the typical segment of ECG signals obtained from normal subject and subject with partial epilepsy are given in Figs. 1 and 2, respectively. It can be noted that the detail wavelet coefficients of the typical segment of ECG signals obtained from normal subject are smaller than the detail wavelet coefficients of the typical segment of ECG signals obtained from subject with partial epilepsy. The detail wavelet coefficients were computed using MATLAB software package. It is possible to apply thresholding at each level of decomposition to reduce the number of coefficients which are used as features representing each segment of the ECG signals. In the present study, in order to reduce the number of wavelet coefficients a stopping criterion for the value of M in Eq. (7) was determined by applying thresholding

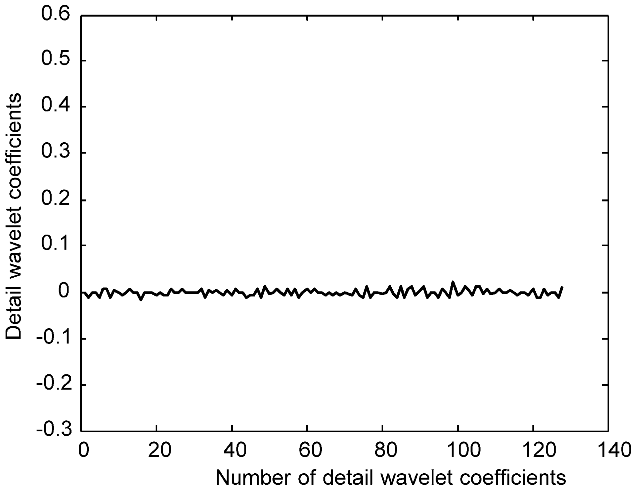

Fig. 1. The 128 detail wavelet coefficients of a typical normal ECG beat.

operation. The decomposition can be represented as

$$x^{(N)} = g^{(N-1)} + g^{(N-2)} + \cdots + g^{(N-M)} + x^{(N-M)}, \tag{7}$$

where the superscript N indicates the level of decomposition, $g^{(\cdot)}$ is called the detail signal. The value of M in Eq. (7) was determined as 4, ignoring the higher levels of decomposition of the WT. At each level of decomposition, the absolute value of the detail signals were measured, and the two coefficients with the highest magnitude were retained. Thus, for $M = 4$, there were $4 \times 2 = 8$ coefficients for each segment of the ECG signals which were used as the ANFIS inputs. The advantage of this method of computing the wavelet coefficients is that the details of the sampled signal $x^{(N)}$ are sorted out and stored in different subspaces, thereby enabling better analysis. This implies that it is possible to delete information of very small magnitudes in each subspace, resulting in much less data information being needed to reconstruct

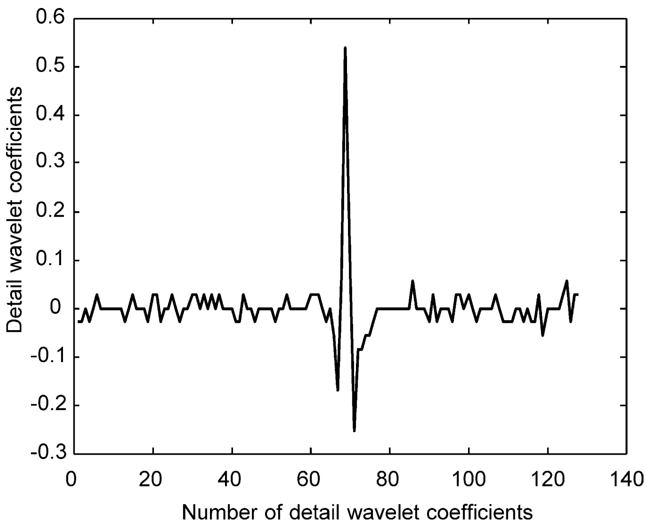

Fig. 2. The 128 detail wavelet coefficients of a typical partial epilepsy ECG beat.

a very good approximation of the original signal (Akay, 1997; Akay & Mello, 1997; Daubechies, 1990; Zhang et al., 2001).

2.2. Adaptive neuro-fuzzy inference system (ANFIS)

2.2.1. Architecture of ANFIS

The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation (Jang, 1992, 1993). Such framework makes the ANFIS modeling more systematic and less reliant on expert knowledge. To present the ANFIS architecture, two fuzzy if–then rules based on a first order Sugeno model are considered:

Rule 1: If (x is A_1) and (y is B_1) then ($f_1 = p_1x + q_1y + r_1$)
Rule 2: If (x is A_2) and (y is B_2) then ($f_2 = p_2x + q_2y + r_2$)

where x and y are the inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region specified by the fuzzy rule, p_i, q_i and r_i are the design parameters that are determined during the training process. The ANFIS architecture to implement these two rules is shown in Fig. 3, in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

In the first layer, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by:

$$O_i^1 = \mu_{A_i}(x) \qquad i = 1,2 \tag{8}$$

$$O_i^1 = \mu_{B_{i-2}}(y) \qquad i = 3,4 \tag{9}$$

where $\mu_{A_i}(x)$, $\mu_{B_{i-2}}(y)$ can adopt any fuzzy membership function. For example, if the bell-shaped membership function is employed, $\mu_{A_i}(x)$ is given by:

$$\mu_{A_i}(x) = \frac{1}{1 + \left\{\left(\frac{x - c_i}{a_i}\right)^2\right\}^{b_i}} \tag{10}$$

where a_i, b_i and c_i are the parameters of the membership function, governing the bell-shaped functions accordingly.

In the second layer, the nodes are fixed nodes. They are labeled with M, indicating that they perform as a simple multiplier. The outputs of this layer can be represented as:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \qquad i = 1,2 \tag{11}$$

which are the so-called firing strengths of the rules.

In the third layer, the nodes are also fixed nodes. They are labeled with N, indicating that they play a normalization role to the firing strengths from the previous layer.

The outputs of this layer can be represented as:

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \qquad i = 1,2 \tag{12}$$

which are the so-called normalized firing strengths.

In the fourth layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial (for a first order Sugeno model). Thus, the outputs of this layer are given by:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i) \qquad i = 1,2 \tag{13}$$

In the fifth layer, there is only one single fixed node labeled with S. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by:

$$O_i^5 = \sum_{i=1}^{2} \bar{w}_i f_i = \frac{\left(\sum_{i=1}^{2} w_i f_i\right)}{w_1 + w_2} \tag{14}$$

It can be observed that there are two adaptive layers in this ANFIS architecture, namely the first layer and the fourth layer. In the first layer, there are three modifiable parameters $\{a_i, b_i, c_i\}$, which are related to the input membership functions. These parameters are the so-called premise parameters. In the fourth layer, there are also three modifiable parameters $\{p_i, q_i, r_i\}$, pertaining to the first order polynomial. These parameters are so-called consequent parameters (Jang, 1992, 1993).

2.2.2. Learning algorithm of ANFIS

The task of the learning algorithm for this architecture is to tune all the modifiable parameters, namely $\{a_i, b_i, c_i\}$ and $\{p_i, q_i, r_i\}$, to make the ANFIS output match the training data. When the premise parameters a_i, b_i and c_i of the membership function are fixed, the output of the ANFIS model can be written as:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \tag{15}$$

Substituting Eq. (12) into Eq. (15) yields:

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2 \tag{16}$$

Substituting the fuzzy if–then rules into Eq. (16), it becomes:

$$f = \bar{w}_1(p_1x + q_1y + r_1) + \bar{w}_2(p_2x + q_2y + r_2) \tag{17}$$

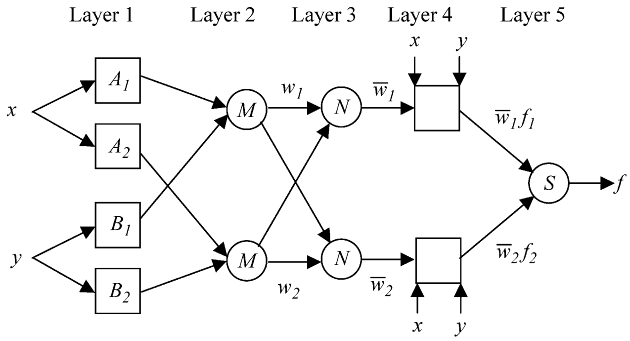

Fig. 3. ANFIS architecture.

After rearrangement, the output can be expressed as:

$$f = (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2 x)p_2 + (\bar{w}_2 y)q_2 + (\bar{w}_2)r_2 \quad (18)$$

which is a linear combination of the modifiable consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2. The least squares method can be used to identify the optimal values of these parameters easily. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard backpropagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS (Jang, 1992, 1993). Therefore, in the present study the proposed ANFIS model was trained with the backpropagation gradient descent method in combination with the least squares method when 8 detail wavelet coefficients defining electrocardiographic changes were used as inputs.

3. Results and discussion

The collection of well-distributed, sufficient, and accurately measured input data is the basic requirement to obtain an accurate model. Selection of the ANFIS inputs is the most important component of designing the classifier based on pattern classification since even the best classifier will perform poorly if the inputs are not selected well. Input selection has two meanings: (1) which components of a pattern, or (2) which set of inputs best represent a given pattern. Since the detail wavelet coefficients contain a significant amount of information about the signal, the detail wavelet coefficients (128 detail wavelet coefficients) of the ECG signals of each subject were computed. From the 128 detail wavelet coefficients a subset of the best 8 coefficients, which were obtained by applying thresholding operation, were used as the ANFIS inputs. Fuzzy set theory plays an important role in dealing with uncertainty when making decisions in medical applications. Using fuzzy logic enabled us to use the uncertainty in the classifier design and consequently to increase the credibility of the system output.

The adequate functioning of ANFIS depends on the sizes of the training set and test set. In this study, training and test sets were formed by 360 vectors (180 vectors from each class) of 8 dimensions (detail wavelet coefficients). The 200 vectors (100 vectors from each class) of 8 dimensions were used for training and the 160 vectors (80 vectors from each class) of 8 dimensions were used for testing. In order to enhance the generalization capability of the ANFIS, the training and the test sets were formed by data obtained from different patients. For both of the beat types, waveform variations were observed among the vectors belonging to the same class.

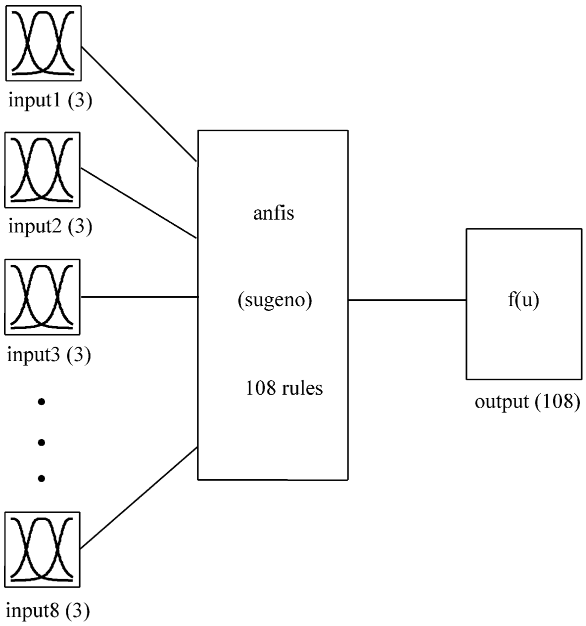

Fig. 4. Fuzzy rule architecture of each ANFIS model. System ANFIS: 8 inputs (detail wavelet coefficients), 1 output, 108 rules.

The training data set was used to train the ANFIS, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained ANFIS model for the detection of electrocardiographic changes in patients with partial epilepsy. Fig. 4 shows the fuzzy rule architecture of the ANFIS using a generalized bell-shaped membership function defined in Eq. (10). There are a total

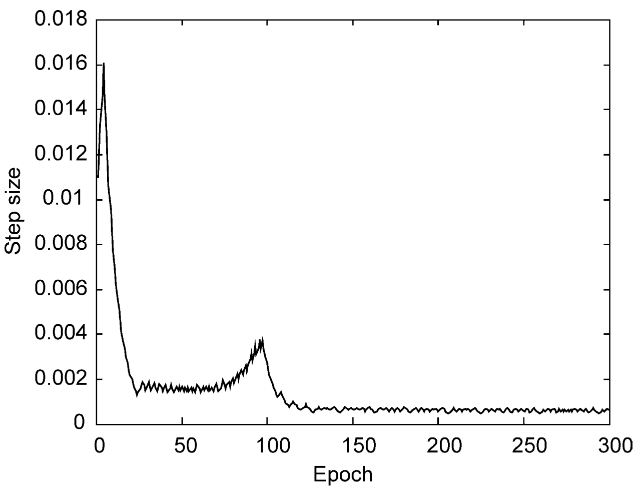

Fig. 5. Adaptation of parameter steps of ANFIS.

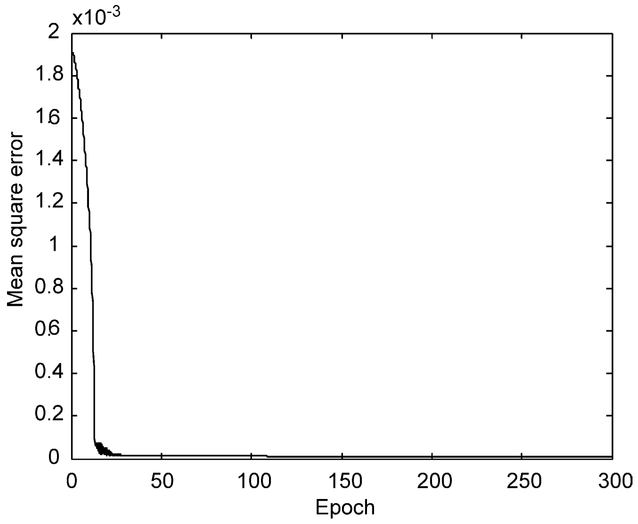

Fig. 6. The curve of network error convergence of ANFIS.

of 108 fuzzy rules in the architecture. The ANFIS shown in Fig. 4 was implemented by using MATLAB software package (MATLAB version 6.0 with fuzzy logic toolbox).

The ANFIS shown in Fig. 4 used 200 training data in 300 training periods and the step size for parameter adaptation had an initial value of 0.011. The steps of parameter adaptation of the ANFIS are shown in Fig. 5. At the end of 300 training periods, the network error convergence curve of ANFIS was derived as shown in Fig. 6. From the curve, the final convergence value is 9.7069×10^{-6}. In a real world domain, just like the one used in the present study, all of the features used in the descriptions of instances may have different levels of relevancy. Therefore, in the present study changes of the final (after training) membership functions with respect to the initial (before training) membership functions of the input parameters were examined. Membership function of each input parameter was divided into three regions, namely, small, medium, and large. The examination of initial and final membership functions indicates that there are considerable changes in the final membership functions of 8 detail wavelet coefficients. Figs. 7 and 8 show the initial and final membership functions of the first and fourth detail wavelet

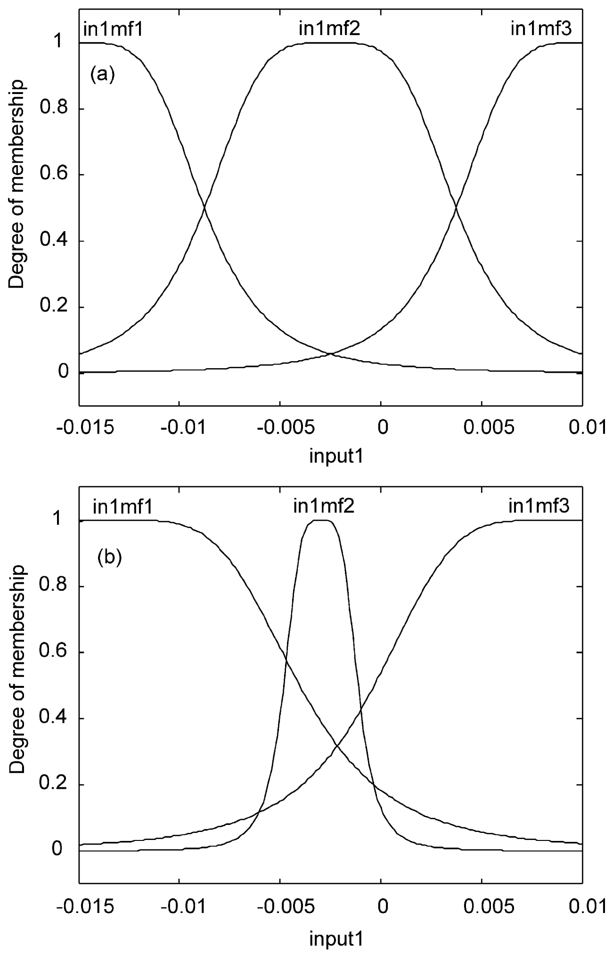

Fig. 7. (a) Initial and (b) final generalized bell-shaped membership function of input 1 (first detail wavelet coefficient).

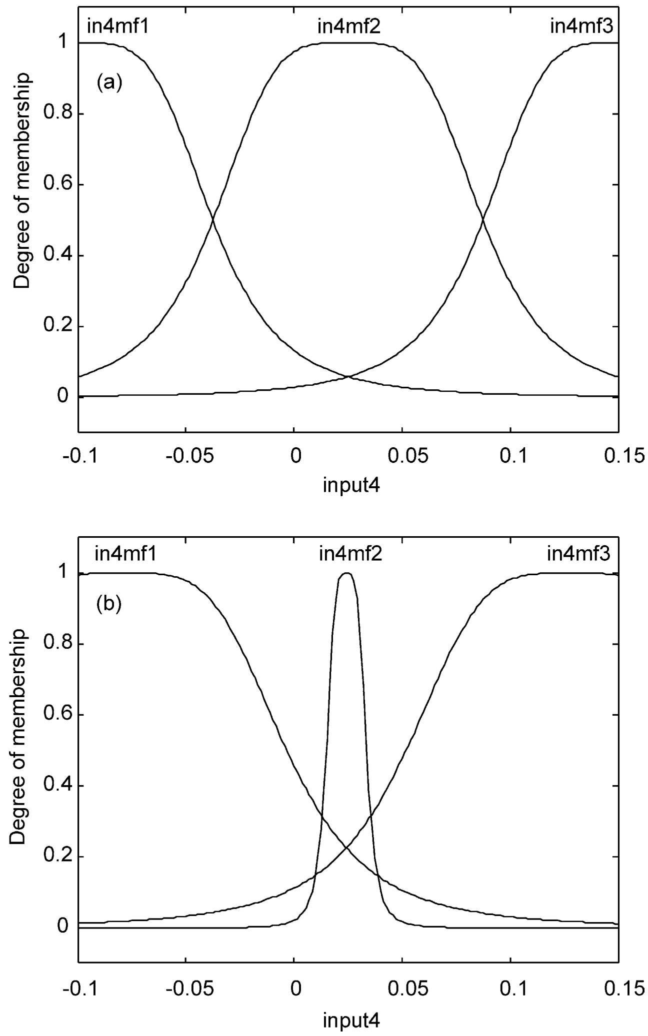

Fig. 8. (a) Initial and (b) final generalized bell-shaped membership function of input 4 (fourth detail wavelet coefficient).

Table 1
The test results of ANFIS

Class of ECG beat	Number of ECG beat	Number of ECG beat classified correctly
Normal	80	79
Partial epilepsy	80	78

Table 2
The values of statistical parameters

Statistical parameters	Values (%)
Specificity	98.75
Sensitivity	97.50
Total classification accuracy	98.13

coefficients (input 1 and input 4) using the generalized bell-shaped membership function, respectively. Based on the analysis of membership functions of each input parameters, it can be mentioned that all of the 8 detail wavelet coefficients have considerable impact on the electrocardiographic changes in patients with partial epilepsy.

After training, 160 testing data was used to validate the accuracy of the ANFIS classifier for the detection of electrocardiographic changes in patients with partial epilepsy. The test results of the ANFIS are presented in Table 1. According to Table 1, 1 normal beat was classified incorrectly by the ANFIS as a partial epilepsy beat and 2 partial epilepsy beats were classified as normal beats.

The test performance of the ANFIS was determined by the computation of the following statistical parameters:

Specificity: number of correct classified normal beats/ number of total normal beats
Sensitivity: number of correct classified partial epilepsy beats/number of total partial epilepsy beats
Total classification accuracy: number of correct classified beats/number of total beats

The values of these statistical parameters are given in Table 2. As it is seen from Table 2, the ANFIS classified normal beats and partial epilepsy beats with the accuracy of 98.75 and 97.50%, respectively. The normal beats and partial epilepsy beats were classified with the accuracy of 98.13%. Based on the correct classification rates, the proposed ANFIS classifier had been found to be successful for the detection of electrocardiographic changes in patients with partial epilepsy.

4. Conclusion

This paper presented a new application of ANFIS classifier for the detection of electrocardiographic changes in patients with partial epilepsy. Fuzzy set theory plays an important role in dealing with uncertainty when making decisions in medical applications. Using fuzzy logic enabled us to use the uncertainty in the classifier design and consequently to increase the credibility of the system output. The proposed technique involved training the ANFIS classifier to detect electrocardiographic changes in patients with partial epilepsy when the detail wavelet coefficients of ECG signals obtained from normal subjects and subjects suffering from partial epilepsy were used as inputs. The presented ANFIS classifier combined the neural network adaptive capabilities and the fuzzy logic qualitative approach. Some conclusions concerning the impacts of features on the detection of electrocardiographic changes in patients with partial epilepsy were obtained through analysis of the ANFIS. The classification results and statistical measures were used for evaluating the ANFIS. The classifications of normal beats, partial epilepsy beats were done with the accuracy of 98.75 and 97.50%, respectively. We therefore have concluded that the proposed ANFIS classifier can be used in detecting electrocardiographic changes in patients with partial epilepsy.

References

Addison, P. S., Watson, J. N., Clegg, G. R., Holzer, M., Sterz, F., & Robertson, C. E. (2000). Evaluating arrhythmias in ECG signals using wavelet transforms. *IEEE Engineering in Medicine and Biology*, *19*(5), 104–109.

Akay, M. (1997). Wavelet applications in medicine. *IEEE Spectrum*, *34*(5), 50–56.

Akay, M.,& Mello, C (1997). Wavelets for biomedical signal processing. *IEEE Proceedings of the 19th Annual International Conference of Engineering in Medicine and Biology Society* (Vol. 6, pp. 2688–2691), Chicago, 30 October–2 November.

Baxt, W. G. (1990). Use of an artificial neural network for data analysis in clinical decision making: The diagnosis of acute coronary occlusion. *Neural Computation*, *2*, 480–489.

Belal, S. Y., Taktak, A. F. G., Nevill, A. J., Spencer, S. A., Roden, D., & Bevan, S. (2002). Automatic detection of distorted plethysmogram pulses in neonates and paediatric patients using an adaptive-network-based fuzzy inference system. *Artificial Intelligence in Medicine*, *24*, 149–165.

Daubechies, I. (1990). The wavelet transform, time-frequency localization and signal analysis. *IEEE Transactions on Information Theory*, *36*(5), 961–1005.

Dokur, Z., & Ölmez, T. (2001). ECG beat classification by a novel hybrid neural network. *Computer Methods and Programs in Biomedicine*, *66*, 167–181.

Dubois, D., & Prade, H. (1998). An introduction to fuzzy systems. *Clinica Chimica Acta*, *270*, 3–29.

Foo, S. Y., Stuart, G., Harvey, B., & Meyer-Baese, A. (2002). Neural network-based EKG pattern recognition. *Engineering Applications of Artificial Intelligence*, *15*, 253–260.

Güler, İ, & Übeyli, E. D (2003). Detection of ophthalmic artery stenosis by least-mean squares backpropagation neural network. *Computers in Biology and Medicine*, *33*(4), 333–343.

Jang, J.-S. R. (1992). Self-learning fuzzy controllers based on temporal backpropagation. *IEEE Transactions on Neural Networks*, *3*(5), 714–723.

Jang, J.-S. R. (1993). ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, and Cybernetics*, *23*(3), 665–685.

Kuncheva, L. I., & Steimann, F. (1999). Fuzzy diagnosis. *Artificial Intelligence in Medicine*, *16*, 121–128.

Kundu, M., Nasipuri, M., Basu, D. K., & Knowledge-based, E. C. G. (2000). interpretation: A critical review. *Pattern Recognition*, *33*, 351–373.

Leutmezer, F., Schernthaner, C., Lurger, S., Pötzelberger, K., & Baumgartner, C. (2003). Electrocardiographic changes at the onset of epileptic seizures. *Epilepsia*, *44*(3), 348–354.

Maglaveras, N., Stamkopoulos, T., Diamantaras, K., Pappas, C., & Strintzis, M. (1998). ECG pattern recognition and classification using non-linear transformations and neural networks: A review. *International Journal of Medical Informatics*, *52*, 191–208.

Miller, A. S., Blott, B. H., & Hames, T. K. (1992). Review of neural network applications in medical imaging and signal processing. *Medical and Biological Engineering and Computing*, *30*, 449–464.

MIT-BIH Database (2003). Available from Massachusetts Institute of Technology, 77 Massachusetts Avenue, Room E25-505A, Cambridge, MA 02139, USA.

Nauck, D., & Kruse, R. (1999). Obtaining interpretable fuzzy classification rules from medical data. *Artificial Intelligence in Medicine*, *16*, 149–169.

Nugent, C. D., Webb, J. A. C., Black, N. D., Wright, G. T. H., & McIntrye, M. (1999). An intelligent framework for the classification of the 12-lead ECG. *Artificial Intelligence in Medicine*, *16*, 205–222.

Opherk, C., Coromilas, J., & Hirsch, L. J. (2002). Heart rate and EKG changes in 102 seizures: Analysis of influencing factors. *Epilepsy Research*, *52*, 117–127.

Rocamora, R., Kurthen, M., Lickfett, L., von Oertzen, J., & Elger, C. E. (2003). Cardiac asystole in epilepsy: Clinical and neurophysiologic features. *Epilepsia*, *44*(2), 179–185.

Saxena, S. C., Kumar, V., & Hamde, S. T. (2002). Feature extraction from ECG signals using wavelet transforms for disease diagnostics. *International Journal of Systems Science*, *33*(13), 1073–1085.

Simon, B. P., & Eswaran, C. (1997). An ECG classifier designed using modified decision based neural networks. *Computers and Biomedical Research*, *30*, 257–272.

Sternickel, K. (2002). Automatic pattern recognition in ECG time series. *Computer Methods and Programs in Biomedicine*, *68*, 109–115.

Tomson, T., Ericson, M., Ihrman, C., & Lindblad, L. E. (1998). Heart rate variability in patients with epilepsy. *Epilepsy Research*, *30*, 77–83.

Übeyli, E. D., & Güler, İ. (2003). Neural network analysis of internal carotid arterial Doppler signals: Predictions of stenosis and occlusion. *Expert Systems with Applications*, *25*(1), 1–13.

Usher, J., Campbell, D., Vohra, J., & Cameron, J. (1999). A fuzzy logic-controlled classifier for use in implantable cardioverter defibrillators. *Pace-Pacing and Clinical Electrophysiology*, *22*, 183–186.

Virant-Klun, I., & Virant, J. (1999). Fuzzy logic alternative for analysis in the biomedical sciences. *Computers and Biomedical Research*, *32*, 305–321.

Zhang, Y., Wang, Y., Wang, W., & Liu, B. (2001). Doppler ultrasound signal denoising based on wavelet frames. *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, *48*(3), 709–716.

Zijlmans, M., Flanagan, D., & Gotman, J. (2002). Heart rate changes and ECG abnormalities during epileptic seizures: Prevalence and definition of an objective clinical sign. *Epilepsia*, *43*(8), 847–854.