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Adaptive Neuro-Fuzzy Inference System For Analysis of Doppler Signals

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Abstract - In this study, a new approach based on adaptive neuro-fuzzy inference system (ANFIS) was presented for detection of ophthalmic artery stenosis. 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. The ophthalmic arterial Doppler signals were recorded from 128 subjects that 62 of them had suffered from ophthalmic artery stenosis and the rest of them had been healthy subjects. Some conclusions concerning the impacts of features on the detection of ophthalmic artery stenosis were obtained through analysis of the ANFIS. The performance of the ANFIS classifier was evaluated in terms of training performance and classification accuracies (total classification accuracy was 97.59%) and the results confirmed that the proposed ANFIS classifier has potential in detecting the ophthalmic artery stenosis.

Key words: Adaptive neuro-fuzzy inference system (ANFIS), Fuzzy logic, Wavelet transform, Doppler signal, Ophthalmic artery stenosis

I. INTRODUCTION

Doppler ultrasound is widely used as a noninvasive method for the assessment of blood flow both in the central and peripheral circulation. It may be used to estimate blood flow, to image regions of blood flow and to locate sites of arterial disease as well as flow characteristics and resistance of ophthalmic arteries [1,2]. Spectral analysis of the Doppler signals produces information concerning the blood flow in the arteries [2,3]. However, artificial neural networks (ANNs) may offer a potentially superior method of Doppler signal analysis to the spectral analysis methods. In contrast to the conventional spectral analysis methods, ANNs not only model the signal, but also make a decision as to the class of signal [4,5]. Furthermore, fuzzy set theory plays an important role in dealing with uncertainty when making decisions in medical applications [6]. 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. A specific approach in neuro-fuzzy development is the adaptive neuro-fuzzy inference system (ANFIS), which has shown significant results in modelling nonlinear functions. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion [7]. Successful implementations of ANFIS in biomedical engineering have been reported, for classification [8] and data analysis [9].

In this study, a new approach based on ANFIS was presented for the detection of ophthalmic artery stenosis. The ANFIS was used to detect ophthalmic artery stenosis when wavelet coefficients defining ophthalmic arterial Doppler signals were used as inputs.

II. FEATURE EXTRACTION USING WAVELET TRANSFORM

All wavelet transforms (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 expressed as a two-scale relation in time domain

$$\begin{aligned} h_{i+1}(k) &= [h]_{\uparrow 2^i} * h_i(k) \\ g_{i+1}(k) &= [g]_{\uparrow 2^i} * h_i(k)\,, \end{aligned} \tag{3}$$

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

$$\begin{aligned} \varphi_{i,l}(k) &= 2^{i/2} h_i(k - 2^i l) \\ \psi_{i,l}(k) &= 2^{i/2} g_i(k - 2^i l)\,, \end{aligned} \tag{4}$$

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

$$\begin{aligned} s_{(i)}(l) &= x(k) * \varphi_{i,l}(k) \\ d_{(i)}(l) &= x(k) * \psi_{i,l}(k)\,, \end{aligned} \tag{5}$$

where $s_{(i)}(l)$ and $d_i(l)$ are the approximation coefficients and the detail coefficients at resolution i, respectively [10].

The smoothing feature of the Daubechies wavelet of order 1 (db1) made it more suitable to detect ophthalmic artery stenosis. Therefore, in the present study the wavelet coefficients were computed using the Daubechies wavelet of order 1. In order to investigate the effect of other wavelets on classifications accuracy, tests were carried out using other wavelets also. Apart from db1, Symmlet of order 10 (sym10), Coiflet of order 4 (coif4), and Daubechies of order 8 (db8) were also tried. It was seen that the Daubechies wavelet offers better accuracy than the others, and db1 is marginally better than db8. The 128 detail wavelet coefficients of ophthalmic arterial Doppler signals obtained from healthy subject (subject no: 10), subject having ophthalmic artery stenosis (subject no: 21) are given in Figs. 1 and 2, respectively. The number of decomposition levels is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlate well with the frequencies required for classification of the signal are retained in the wavelet coefficients. In the present study, since the Doppler signals do not have any useful frequency components below 40 Hz, the number of decomposition levels was chosen to be 7. Thus, the ophthalmic arterial Doppler signals were decomposed into the details $D_1 - D_7$ and one final approximation, A_7.

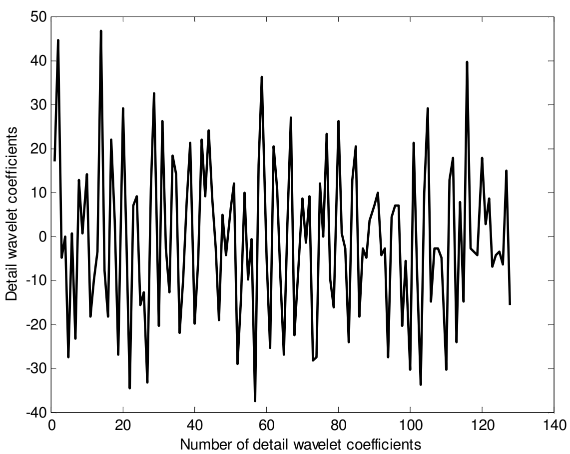

Fig. 1. Detail wavelet coefficients of ophthalmic arterial Doppler signals obtained from healthy subject (subject no: 10)

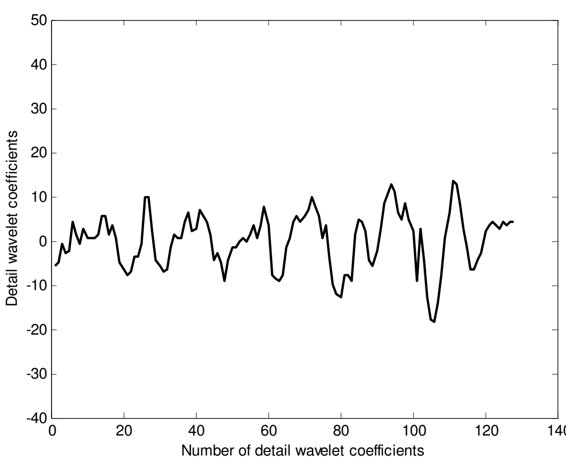

Fig. 2. Detail wavelet coefficients of ophthalmic arterial Doppler signals obtained from subject having ophthalmic artery stenosis (subject no: 21)

It is possible to apply thresholding at each level of decomposition to reduce the number of coefficients which are used as features representing ophthalmic arterial Doppler signals. In the present study, in order to reduce the number of wavelet coefficients thresholding operation was applied. The advantage of this method of computing the wavelet coefficients is that the details of the sampled signal are sorted out and stored in different subspaces, thereby enabling better analysis [10,11]. At each level of decomposition, the absolute value of the detail signals were measured, and the coefficients with the highest magnitude were retained. Thus, 8 coefficients were used as the ANFIS inputs for each ophthalmic arterial Doppler signal.

III. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation [7]. 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

($f_1 = p_1 x + q_1 y + r_1$)

Rule 2: If (x is A_2) and (y is B_2) then

($f_2 = p_2 x + q_2 y + r_2$)

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 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. A hybrid algorithm combining the least squares method and the gradient descent method can be used to identify the optimal values of these parameters easily. 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 ophthalmic arterial Doppler signals were used as inputs.

IV. RESULTS AND DISCUSSION

The collection of well-distributed, sufficient, and accurately measured input data is the basic requirement to obtain an accurate model. Since the detail wavelet coefficients contain a significant amount of information about the signal, the detail wavelet coefficients (128 detail wavelet coefficients) of the ophthalmic arterial Doppler 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.

Various experiments were performed and the sizes of the training and testing sets were determined by taking into consideration the classification accuracies. The data set was divided into two separate data sets – the training data set (45 subjects) and the testing data set (83 subjects). 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 ophthalmic artery stenosis. There were a total of 108 fuzzy rules in the architecture of the ANFIS using a generalized bell shaped membership function. The ANFIS was implemented by using MATLAB software package (MATLAB version 6.0 with fuzzy logic toolbox). The ANFIS used 45 training data in 350 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. 3. At the end of 350 training periods, the network error convergence curve of ANFIS was derived as shown in Fig. 4. From the curve, the final convergence value is 3.4159×10^{-6}.

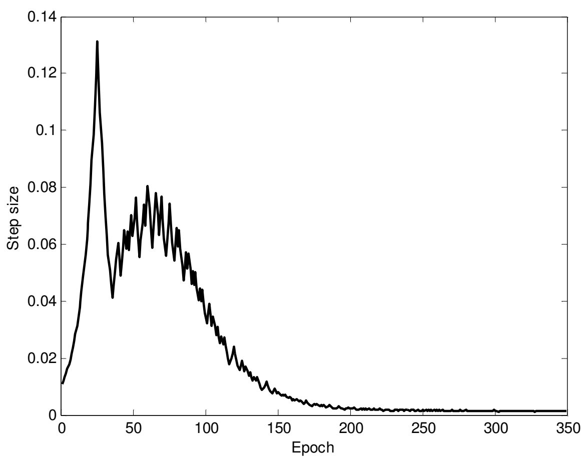

Fig. 3. Adaptation of parameter steps of ANFIS

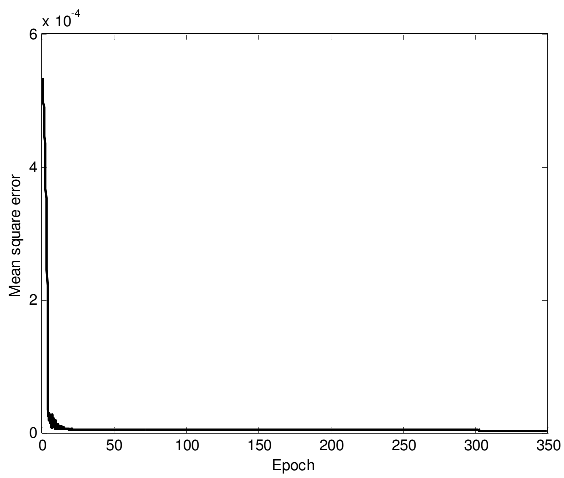

Fig. 4. The curve of network error convergence of ANFIS

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. Fig. 5 shows the initial and final membership function of the first detail wavelet coefficient (input 1) using the generalized bell shaped membership function. 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 detection of ophthalmic artery stenosis.

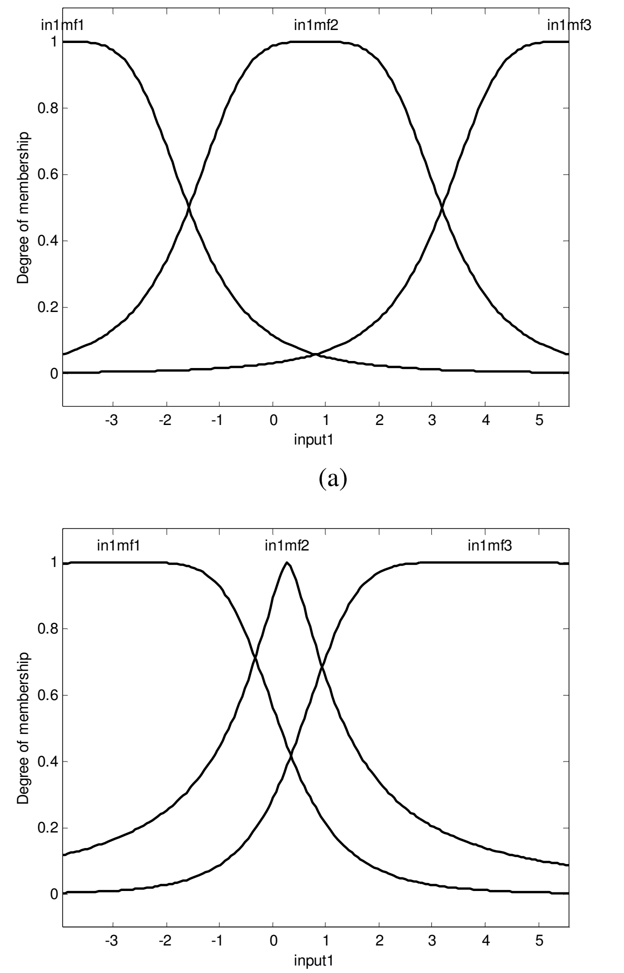

Fig. 5. (a) Initial and (b) final generalized bell shaped membership function of input 1 (first detail wavelet coefficient)

After training, 83 testing data was used to validate the accuracy of the ANFIS classifier for the detection of ophthalmic artery stenosis. The test results of the ANFIS are presented in Table I. According to Table I, 1 normal subject was classified incorrectly by the ANFIS as a subject having ophthalmic artery stenosis and 1 subject having ophthalmic artery stenosis was classified as a normal subject. The test performance of the ANFIS was determined by the computation of the statistical parameters such as specificity, sensitivity and accuracy. The values of these statistical parameters are given in Table II. As it is seen from Table II, the ANFIS classified normal subjects and subjects having stenosis with the accuracy of 97.67% and 97.50%, respectively. The normal subjects and subjects having stenosis were classified with the accuracy of 97.59%.

TABLE I
THE TEST RESULTS OF ANFIS

Ophthalmic artery condition	Number of subjects	Number of subjects classified correctly
Normal	43	42
Stenosis	40	39

TABLE II
THE VALUES OF STATISTICAL PARAMETERS

Statistical parameters	Values
Specificity	97.67%
Sensitivity	97.50%
Accuracy	97.59%

V. CONCLUSION

This paper presented a new application of ANFIS classifier for the detection of ophthalmic artery stenosis. 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 ophthalmic artery stenosis when the detail wavelet coefficients of ophthalmic arterial Doppler signals obtained from normal subjects and subjects having stenosis 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 ophthalmic artery stenosis were obtained through analysis of the ANFIS. The classification results and statistical measures were used for evaluating the ANFIS. The classifications of normal subjects, subjects having stenosis were done with the accuracy of 97.67% and 97.50%, respectively. These results demonstrated that the proposed ANFIS classifier can be used in detecting ophthalmic artery stenosis.

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