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Elif Derya UBEYLI, İnan GÜLER APPLICATION OF ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM FOR ANALYSIS OF OPHTHALMIC ARTERIAL DOPPLER SIGNALS USING FEATURE EXTRACTION

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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 suffered from ophthalmic artery stenosis and the rest of them were 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 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,

1. 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.

2. MATERIALS AND METHOD

2.1. 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:

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

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

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

A sequence of filters with increasing length (indexed by i) can be expressed as a two-scale relation in time domain

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

where the $[\cdot]_{1\uparrow m}$ subscript 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

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

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

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

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 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.

2.2. 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 ($f_1=p_1x+q_1y+r_1$)

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

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. 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

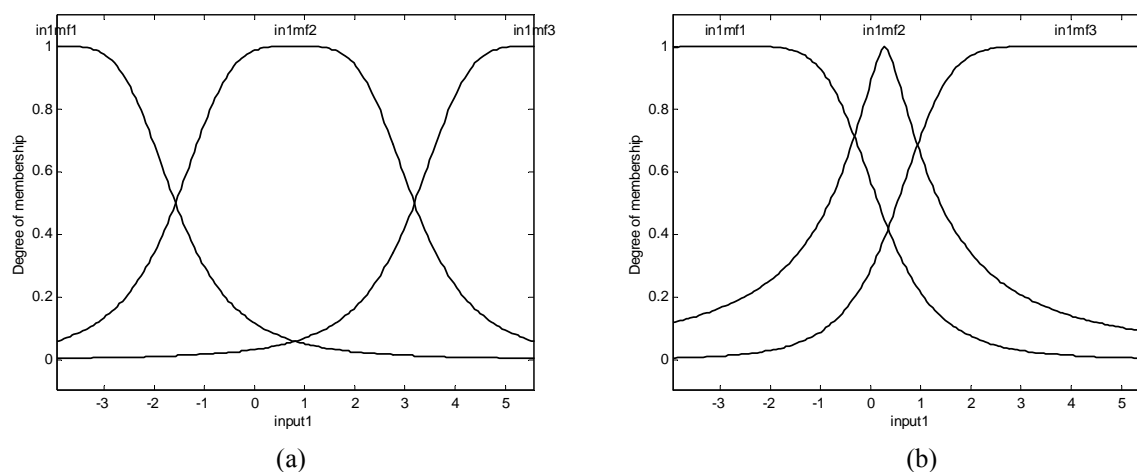


Figure 1. (a) Initial and (b) final generalized bell shaped membership function of input 1 (first detail wavelet coefficient)

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.

3. 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

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. At the end of 350 training periods, the network error convergence curve of ANFIS was derived and the final convergence value was 3.4159×10^{-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. Figure 1 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.

After training, 83 testing data was used to validate the accuracy of the ANFIS classifier for the detection of ophthalmic artery stenosis. 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. Using fuzzy logic enabled us to use the uncertainty in the classifier design and consequently to increase the credibility of the system output. We therefore have concluded that the proposed ANFIS classifier can be used in detecting ophthalmic artery stenosis.

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