Adaptive neuro-fuzzy inference systems for analysis of internal carotid arterial 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 internal carotid artery stenosis and occlusion. The internal carotid arterial Doppler signals were recorded from 130 subjects that 45 of them suffered from internal carotid artery stenosis, 44 of them suffered from internal carotid artery occlusion and the rest of them were healthy subjects. The three ANFIS classifiers were used to detect internal carotid artery conditions (normal, stenosis and occlusion) when two features, resistivity and pulsatility indices, defining changes of internal carotid arterial Doppler waveforms were used as inputs. To improve diagnostic accuracy, the fourth ANFIS classifier (combining ANFIS) was trained using the outputs of the three ANFIS classifiers as input data. 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 internal carotid artery stenosis and occlusion were obtained through analysis of the ANFIS. The performance of the ANFIS model was evaluated in terms of classification accuracies and the results confirmed that the proposed ANFIS classifiers have some potential in detecting the internal carotid artery stenosis and occlusion. The ANFIS model achieved accuracy rates which were higher than that of the stand-alone neural network model.

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Keywords: Adaptive neuro-fuzzy inference system; Fuzzy logic; Doppler signal; Internal carotid artery; Stenosis; Occlusion

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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 internal carotid arteries [1–4]. Doppler systems are based on the principle that ultrasound, emitted by an ultrasonic transducer, is returned partially towards the transducer by the moving targets, thereby inducing a shift in frequency proportional to the emitted frequency and the velocity along the ultrasound beam. The results of the studies in the literature have shown that Doppler ultrasound evaluation can give reliable information on both systolic and diastolic blood velocities of arteries and have supported that Doppler ultrasound is useful in screening certain hemodynamic alterations in arteries [1–4].

Spectral analysis of the Doppler signals produces information concerning the blood flow in the arteries [3,5]. 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 [6–9]. Furthermore, 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 [10–12]. 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 modelling 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 [13,14]. Successful implementations of ANFIS in biomedical engineering have been reported, for classification [15,16] and data analysis [17].

In this study, a new approach based on ANFIS was presented for the detection of internal carotid artery stenosis and occlusion. Three ANFIS classifiers were used to detect internal carotid artery conditions (normal, stenosis and occlusion) when two features, resistivity and pulsatility indices, defining changes of internal carotid arterial Doppler waveforms were used as inputs. Each of the ANFIS classifier was trained so that they are likely to be more accurate for one type of internal carotid artery condition than the other conditions. The predictions of the three ANFIS classifiers were combined by the fourth ANFIS classifier. The internal carotid arterial Doppler signals obtained from healthy subjects, subjects having internal carotid artery stenosis and occlusion. The proposed ANFIS model was then evaluated and performance of the ANFIS model was reported. We were able to achieve significant improvement in accuracy by applying ANFIS model compared to the stand-alone neural networks. Finally, some conclusions were drawn concerning the impacts of features on the detection of internal carotid artery stenosis and occlusion.

2. Materials and method

The procedure used in the development of the classification system consists of four parts: (i) measurement of internal carotid arterial Doppler signals, (ii) feature extraction from Doppler waveforms
(resistivity and pulsatility indices), (iii) classification using the ANFIS trained with the backpropagation gradient descent method in combination with the least-squares method, (iv) classification results (normal internal carotid artery, stenosis in internal carotid artery, occlusion in internal carotid artery). These procedures are explained in the remainder of this paper.

2.1. Subjects

In the present study, internal carotid arterial Doppler signals were obtained from 130 subjects. The group was consisted of 62 females and 68 males with ages ranging from 18 to 65 years and a mean age of 34.5 years (standard deviation-SD 9.4). Toshiba 140A color Doppler ultrasonography was used during examinations and sonograms were taken into consideration. According to examination results, 45 of 130 subjects suffered from internal carotid artery stenosis, 44 of them suffered from internal carotid artery occlusion and the rest of them were healthy subjects. The group having internal carotid artery stenosis was consisted of 22 females and 23 males with a mean age 38.5 years (SD 8.2, range 24–62), the group having internal carotid artery occlusion was consisted of 21 females and 23 males with a mean age 39.0 years (SD 8.7, range 27–65) and the healthy subjects were consisted of 19 females and 22 males with a mean age 35.0 years (SD 8.5, range 18–60).

2.2. Measurement of internal carotid arterial Doppler signals

Internal carotid artery examinations were performed with a Doppler unit using a 5 MHz ultrasonic transducer. The block diagram of the measurement system is shown in Fig. 1. The system consists of five units. These are 5 MHz ultrasonic transducer, analog Doppler unit (Toshiba 140A Color Doppler Ultrasonography), recorder (Sony), analog/digital interface board (Sound Blaster Pro-16 bit), a personal computer with a printer. The ultrasonic transducer was applied on a horizontal plane to the neck using water-soluble gel as a coupling gel. Care was taken not to apply pressure to the neck in order to avoid artifacts. The probe was most often placed at an angle of 60° towards the internal carotid artery.

2.3. Feature extraction from Doppler waveforms

The Doppler power spectrum has a shape similar to the histogram of the blood velocities within the sample volume and thus spectral analysis of the Doppler signal produces information concerning the velocity distribution in the artery [1–4]. The estimation of the power spectral density of the Doppler signal is performed by applying spectral analysis methods. By using spectral analysis methods, the variations in the shape of the Doppler power spectra as a function of time are presented in the form of sonograms [1–5]. In a sonogram, the horizontal axis ($t$) represents time, the vertical axis ($f$) frequency and the gray level
intensity at coordinates \((t, f)\) denotes signal power at frequency \(f\) and time instant \(t\). The darker the gray level at coordinates \((t, f)\), the higher the power of the frequency component \(f\) measured at time instant \(t\). By monitoring the sonogram, variation of the spectral properties of the Doppler signal and a number of extents related to the blood flow can easily be tracked. Sonograms of the internal carotid arterial Doppler signals obtained from 33-year-old healthy subject, 35-year-old unhealthy subject having internal carotid artery stenosis, and 36-year-old unhealthy subject having internal carotid artery occlusion are shown in Fig. 2 [8].

Feature extraction is a process of pattern recognition and consists of extracting and combining salient features of the pattern vector into a feature vector (for example resistivity index or pulsatility index). Then decision is given whether such a feature vector is obtained from a normal or abnormal artery. Waveform indices such as resistivity index (RI) and pulsatility index (PI) can be used for evaluation of internal carotid arterial Doppler waveforms. Both the RI and PI are reflections of the resistance to flow, downstream from the point of insonation. They are influenced by many factors including proximal stenosis, distal stenosis and peripheral resistance. RI and PI are defined as

\[
RI = \frac{S - D}{S},
\]

\[
PI = \frac{S - D}{M},
\]

where \(S\) is maximum systolic height, \(D\) is end diastolic height and \(M\) is mean height of the waveform as shown in Fig. 3 [1,8].

2.4. Adaptive neuro-fuzzy inference system (ANFIS)

2.4.1. Architecture of ANFIS

The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation [13,14]. 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 ANFIS architecture to implement these two rules is shown in Fig. 4, 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

\[
O_i^1 = \mu_{A_i}(x), \quad i = 1, 2,
\]

\[
O_i^1 = \mu_{B_i-2}(y), \quad i = 3, 4,
\]
Fig. 2. Sonograms of the internal carotid arterial Doppler signals recorded from: (a) 33-year-old healthy subject (subject no: 12), (b) 35-year-old unhealthy subject having internal carotid artery stenosis (subject no: 25), (c) 36-year-old unhealthy subject having internal carotid artery occlusion (subject no: 38).
Fig. 3. Diagram illustrating the variables involved in the definitions of resistivity index and pulsatility index. \( S \) is maximum systolic height, \( D \) is end diastolic height and \( M \) is mean height of the Doppler waveform.

\[
\text{Time (s)} \quad \text{Doppler shift Frequency (Hz)}
\]

\( S \) is maximum systolic height, \( D \) is end diastolic height and \( M \) is mean height of the Doppler waveform.

Fig. 4. ANFIS architecture.

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

\[
\mu_{A_i}(x) = \frac{1}{1 + \left\{ \left( \frac{x - c_i}{a_i} \right)^2 \right\}^{b_i}},
\]

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

\[
O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1, 2
\]

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
\[ O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \]  
(7)
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
\[ O_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i), \quad i = 1, 2. \]  
(8)

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
\[ O_5 = \sum_{i=1}^{2} \bar{w}_i f_i = \frac{\left( \sum_{i=1}^{2} w_i f_i \right)}{w_1 + w_2}. \]  
(9)

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 [13,14].

2.4.2. 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
\[ f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2. \]  
(10)

Substituting Eq. (7) into Eq. (10) yields
\[ f = \bar{w}_1 f_1 + \bar{w}_2 f_2. \]  
(11)

Substituting the fuzzy if–then rules into Eq. (11), it becomes
\[ f = \bar{w}_1 (p_1 x + q_1 y + r_1) + \bar{w}_2 (p_2 x + q_2 y + r_2). \]  
(12)

After rearrangement, the output can be expressed as
\[ f = (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2 x)p_2 + (\bar{w}_2 y)q_2 + (\bar{w}_2)r_2 \]  
(13)
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 [13,14]. Therefore, in the present study the proposed ANFIS model was trained with the backpropagation gradient descent method in combination with the least-squares method.

3. Results and discussion

The collection of well-distributed, sufficient, and accurately measured input data is the basic requirement to obtain an accurate model. The proposed technique involved training three ANFIS classifiers to detect internal carotid artery condition when the RI and PI values of 130 subjects were used as inputs. We trained the three ANFIS classifiers since there were three possible outcomes of the diagnosis of internal carotid artery conditions (normal, stenosis and occlusion). Each of the ANFIS classifier was trained so that they are likely to be more accurate for one type of internal carotid artery condition than the other conditions. The values of RI and PI for the three groups (normal, stenosis and occlusion) of subjects are given in Table 1 and are plotted in Figs. 5 and 6, respectively. As we have mentioned in our previous study [8], Table 1, Figs. 5 and 6 show that it is difficult to separate the normal, stenosis and occlusion subjects using the values of the RI and PI. Since there is a considerable overlap in the RI and PI values of normal, stenosis and occlusion groups, 129 points of the logarithm of the internal carotid artery Doppler spectrum were used as the multilayer perceptron neural network (MLPNN) inputs in our previous study [8]. However, fuzzy set theory plays an important role in dealing with uncertainty when making decisions in medical applications. Therefore, we chose fuzzy logic in the present study due to the uncertainty in internal carotid arterial Doppler signals classification, which is a result of imprecise boundaries between RI and PI values of normal, stenosis and occlusion groups. Using fuzzy logic enabled us to use the uncertainty in the classifier design and consequently to increase the credibility of the system output. Samples with target outputs normal, stenosis and occlusion were given the binary target values of (0,0,1), (0,1,0), (1,0,0), respectively. We trained the fourth ANFIS classifier to combine the predictions of the three ANFIS classifiers. The outputs of the three ANFIS classifiers were used as the inputs of the fourth ANFIS classifier. Since the number of inputs used in the ANFIS model was much less than the number of inputs used in the MLPNN presented in our previous study [8], the response time of ANFIS model was much less than that of the MLPNN.

The data set was divided into two separate data sets—the training data set (42 subjects) and the testing data set (88 subjects). The training data set was used to train each ANFIS classifier, whereas the testing data set was used to verify the accuracy and the effectiveness of each trained ANFIS model for the detection of internal carotid artery stenosis and occlusion. Fig. 7 shows the fuzzy rule architecture of each ANFIS using a generalized bell shaped membership function defined in Eq. (5). There are a total of 27 fuzzy rules in the architecture. Fig. 8 shows the fuzzy rule architecture of the combining ANFIS classifier (the fourth ANFIS classifier) using a generalized bell shaped
Table 1
RI and PI values of normal subjects and subjects having internal carotid artery stenosis and occlusion

<table>
<thead>
<tr>
<th>Subject no</th>
<th>Condition</th>
<th>RI</th>
<th>PI</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>Normal</td>
<td>0.56</td>
<td>1.15</td>
</tr>
<tr>
<td>19</td>
<td>Normal</td>
<td>0.64</td>
<td>1.30</td>
</tr>
<tr>
<td>25</td>
<td>Stenosis</td>
<td>0.65</td>
<td>1.32</td>
</tr>
<tr>
<td>32</td>
<td>Stenosis</td>
<td>0.71</td>
<td>1.39</td>
</tr>
<tr>
<td>38</td>
<td>Occlusion</td>
<td>0.69</td>
<td>1.37</td>
</tr>
<tr>
<td>47</td>
<td>Occlusion</td>
<td>0.80</td>
<td>1.42</td>
</tr>
<tr>
<td>54</td>
<td>Normal</td>
<td>0.69</td>
<td>1.34</td>
</tr>
<tr>
<td>61</td>
<td>Stenosis</td>
<td>0.81</td>
<td>1.41</td>
</tr>
<tr>
<td>72</td>
<td>Occlusion</td>
<td>0.90</td>
<td>1.60</td>
</tr>
<tr>
<td>81</td>
<td>Normal</td>
<td>0.66</td>
<td>1.32</td>
</tr>
<tr>
<td>94</td>
<td>Stenosis</td>
<td>0.67</td>
<td>1.31</td>
</tr>
<tr>
<td>109</td>
<td>Occlusion</td>
<td>0.81</td>
<td>1.45</td>
</tr>
</tbody>
</table>

Fig. 5. Resistivity index values for normal, stenosis and occlusion groups.

Fig. 6. Pulsatility index values for normal, stenosis and occlusion groups.

membership function. There are a total of 30 fuzzy rules in the architecture. Each ANFIS shown in Figs. 7 and 8 was implemented by using MATLAB software package (MATLAB version 6.0 with fuzzy logic toolbox).
Each ANFIS shown in Figs. 7 and 8 used 42 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 each ANFIS are shown in Fig. 9. At the end of 350 training periods, the network error convergence curve of each ANFIS was derived as shown in Fig. 10. From the curve, the final convergence value is \(2.162 \times 10^{-6}\). However, in our previous study [8] the MLPNN trained with the backpropagation algorithm had a slow convergence and mean square error converged to a small constant approximately zero in 5000 epochs. Thus, the convergence rate of each ANFIS classifier presented in this study was found to be higher than the neural network model used in the previous study [8].

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) generalized bell shaped membership functions with respect to the initial (before training) membership functions of the input parameters were examined. Matlab function, gbellmf (generalized bell curve membership function), was used to generate membership functions. 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 RI (input 1) and PI (input 2). Figs. 11 and 12 show the initial and final membership functions of the RI and PI values using the generalized bell shaped membership function, respectively. This analysis was done since the amount of changes in the final membership functions of inputs indicates the impact of inputs on the detection of output. Based on the analysis of membership
functions, it can be mentioned that both RI and PI values have considerable impact on the detection of internal carotid artery stenosis and occlusion.

After training, 88 testing data was used to validate the accuracy of ANFIS model for the detection of internal carotid artery stenosis and occlusion. The testing data set was consisted of 28 normal subjects, 31 subjects having internal carotid artery stenosis and 29 subjects having internal carotid artery occlusion. In classification, the aim is to assign the input patterns to one of several classes, usually represented by outputs restricted to lie in the range from 0 to 1, so that they represent the probability of class membership. While the classification is carried out, a specific pattern is assigned to a specific class according to the characteristic features selected for it. In this application, there were three classes: normal, stenosis and occlusion. Classification results of the ANFIS model were displayed by a confusion matrix. The confusion
Fig. 11. (a) Initial and (b) final generalized bell shaped membership function of input 1 (RI).
Fig. 12. (a) Initial and (b) final generalized bell shaped membership function of input 2 (PI).
Table 2
The values of statistical parameters of the ANFIS model

<table>
<thead>
<tr>
<th>Statistical parameters</th>
<th>Values (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specificity</td>
<td>96.43</td>
</tr>
<tr>
<td>Sensitivity (stenosis)</td>
<td>96.77</td>
</tr>
<tr>
<td>Sensitivity (occlusion)</td>
<td>96.55</td>
</tr>
<tr>
<td>Total classification accuracy</td>
<td>96.59</td>
</tr>
</tbody>
</table>

The confuson matrix showing the classification results of the ANFIS model is given below.

<table>
<thead>
<tr>
<th>Output/ Desired</th>
<th>Result (Normal)</th>
<th>Result (Stenosis)</th>
<th>Result (Occlusion)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Result (Normal)</td>
<td>27</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Result (Stenosis)</td>
<td>1</td>
<td>30</td>
<td>1</td>
</tr>
<tr>
<td>Result (Occlusion)</td>
<td>0</td>
<td>0</td>
<td>28</td>
</tr>
</tbody>
</table>

According to the confusion matrix, 1 normal subject was classified incorrectly by the ANFIS model as a subject suffering from stenosis, 1 subject suffering from stenosis was classified as a normal subject, 1 subject suffering from occlusion was classified as a subject suffering from stenosis. The test performance of the ANFIS model was determined by the computation of the following statistical parameters:

Specificity: number of correct classified normal subjects/number of total normal subjects

Sensitivity (stenosis): number of correct classified subjects having stenosis/number of total subjects having stenosis

Sensitivity (occlusion): number of correct classified subjects having occlusion/number of total subjects having occlusion

Total classification accuracy: number of correct classified subjects/number of total subjects

The values of these statistical parameters are given in Table 2. As it is seen from Table 2, the ANFIS model classified normal subjects and subjects suffering from stenosis and occlusion with the accuracy of 96.43%, 96.77%, 96.55%, respectively. The normal subjects, subjects suffering from stenosis and occlusion were classified with the accuracy of 96.59%. The correct classification rates of the stand-alone neural network (MLPNN) presented in our previous study [8] were 95.24% for normal subjects, 91.30% for subjects suffering from stenosis, and 91.67% for subjects suffering from occlusion. The total
classification accuracy of the stand-alone neural network was 92.65%. Thus, the accuracy rates of the ANFIS model presented for this application were found to be higher than that of the stand-alone neural network model. These results indicate that the proposed ANFIS model has some potential in detecting internal carotid artery stenosis and occlusion.

4. Conclusion

This paper presented a new application of ANFIS model for the detection of internal carotid artery stenosis and occlusion. We chose fuzzy logic in the present study due to the uncertainty in internal carotid arterial Doppler signals classification, which is a result of imprecise boundaries between three classes ‘normal’, ‘stenosis’ and ‘occlusion’. Using fuzzy logic enabled us to use this uncertainty in the classifier design and consequently to increase the credibility of the system output. The proposed technique involved training the three ANFIS classifiers to detect internal carotid artery stenosis and occlusion when the RI and PI values of 130 subjects were used as inputs. The predictions of the three ANFIS classifiers were combined by the fourth ANFIS classifier. The presented 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 internal carotid artery stenosis and occlusion were obtained through analysis of the ANFIS. The classification results were used for evaluating the ANFIS classifiers. The total classification accuracy of the ANFIS model was 96.59%. We therefore have concluded that the proposed ANFIS model can be used in detecting internal carotid artery stenosis and occlusion by taking into consideration the misclassification rates.

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References


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