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Detecting variability of internal carotid arterial Doppler signals by Lyapunov exponents

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Abstract

The new method presented in this study was directly based on the consideration that internal carotid arterial Doppler signals are chaotic signals. This consideration was tested successfully using the nonlinear dynamics tools, like the computation of Lyapunov exponents. Multilayer perceptron neural network (MLPNN) architecture was formulated and used as a basis for detecting variabilities such as stenosis and occlusion in the physical state of internal carotid arterial Doppler signals. The computed Lyapunov exponents of the internal carotid arterial Doppler signals were used as inputs of the MLPNN. Receiver operating characteristic (ROC) curve was used to assess the performance of the detection process. The internal carotid arterial Doppler signals were classified with the accuracy varying from 94.87% to 97.44%. The results confirmed that the proposed MLPNN trained with Levenberg–Marquardt algorithm has potential in detecting stenosis and occlusion in internal carotid arteries.

Keywords: Doppler signals; Internal carotid artery stenosis; Internal carotid artery occlusion; Chaotic signal; Lyapunov exponents; Multilayer perceptron neural network (MLPNN); Levenberg–Marquardt algorithm

1. Introductıon

Doppler ultrasound is widely used as a noninvasive method for the assessment of blood flow both in the central and peripheral circulation [1,2]. 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 [3–5]. 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 [1–5].

Spectral analysis of the Doppler signals produces information concerning the blood flow in the arteries [3–6]. Conventional spectral analysis techniques have been used extensively in modelling Doppler signals over the last two decades. However, the conventional spectral analysis techniques assume stationary data, but the Doppler signals are generally more complex. Therefore, the Doppler signals have been considered as chaotic signals with complex nonlinear characteristics arising from deterministic physical processes [7–9]. To extract physical information from the chaotic model and to be able to associate them with, for example, the hemodynamics and hematological phenomena of blood, one or both of the following two approaches are tracked. The first is to estimate an explicit form of a global equation of motion (for example, a set of differential or difference equations) of the Doppler signals. This may lead to a link between the parameters of the resultant model and the physical state of blood. The

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second approach is to compute parameters such as Lyapunov exponents and to study them under different hemodynamic and hematological conditions of blood flow [7–9]. However, these approaches require a signal with very high resolution and very low noise level to be able to use the small-scale changes in these parameters that would take place as a result of variabilities in the physical state of the Doppler signals. Therefore, in the present study the internal carotid arterial Doppler signals were high-pass filtered to remove high-amplitude, low-frequency components attributable to vessel wall movement.

Doppler ultrasound demonstrates the flow characteristics and resistance of internal carotid arteries in various disorders such as stenosis and occlusion [3–5]. Internal carotid artery disease is a form of disease that affects the vessels leading to the head and brain (cerebrovascular disease). Internal carotid artery disease usually occurs due to the build up of fatty material and plaque. Symptomatic internal carotid artery plaques are characterized by increased cellular proliferation, lipid accumulation, calcification, hemorrhage, and thrombosis. Stenosis and occlusions in the internal carotid artery due to internal carotid artery plaques might be observed symptoms during the detection of internal carotid artery disease [10,11]. Since a stroke most often occurs when the internal carotid arteries become blocked and the brain does not get enough oxygen, early detection of changes in internal carotid artery is important.

In this study, an experimental investigation was presented, targeted at detecting variabilities such as stenosis and occlusion in the physical state of internal carotid arterial Doppler signals. Toward achieving this aim, the internal carotid arterial Doppler signals were considered as chaotic signals and this consideration was tested successfully using the nonlinear dynamics tool in the literature, the computation of Lyapunov exponents. This was the basis for the automatic detection of internal carotid artery stenosis and occlusion. More specifically, the internal carotid arterial Doppler signals were modelled using a multilayer perceptron neural network (MLPNN). Since flow in arteries is pulsatile and the moving targets have a random spatial distribution, the Doppler signal is time-varying and random. Therefore, the computed Lyapunov exponents of the internal carotid arterial Doppler signals were used as inputs of the MLPNN. The MLPNN presented in this study was trained, cross validated and tested with the computed Lyapunov exponents of the internal carotid arterial Doppler signals obtained from healthy subjects, subjects suffering from internal carotid artery stenosis, and subjects suffering from internal carotid artery occlusion. In order to improve convergence rate, the MLPNN trained with the Levenberg–Marquardt algorithm. The correct classification rates and convergence rate of the neural network model presented in this study were found to be high.

2. Materials and methods

The procedure used in the development of the classification system consisted of four parts: (i) measurement of internal carotid arterial Doppler signals, (ii) feature extraction by computing Lyapunov exponents (128 Lyapunov exponents and the first 80 Lyapunov exponents selected as neural network inputs), (iii) classification using the MLPNN trained with the Levenberg–Marquardt algorithm, (iv) classification results (healthy subjects, subjects suffering from internal carotid artery stenosis, subjects suffering from internal carotid artery occlusion). 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 160 subjects. The group consisted of 78 females and 82 males with ages ranging from 18 to 67 years and a mean age of 32.0 years (standard deviation (SD) 9.6). Toshiba 140A color Doppler ultrasonography was used during examinations and sonograms were taken into consideration. The internal carotid arterial Doppler signals used in this study were obtained from Medical Faculty Hospital of Erciyes University and the usage of the data in our study was approved by the ethic board of the institution. According to the examination results, 59 of the 160 subjects suffered from internal carotid artery stenosis, 53 of them suffered from internal carotid artery occlusion, and the rest were healthy subjects (control group) who had no arterial disease. The group suffering from internal carotid artery stenosis consisted of 26 females and 33 males with a mean age 33.0 years (SD 8.6, range 21–67), the group suffering from internal carotid artery occlusion consisted of 29 females and 24 males with a mean age 32.5 years (SD 8.5, range 20–65), and the healthy subjects were 23 females and 25 males with a mean age 31.5 years (SD 9.4, range 18–65).

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 consisted of five units. These were 5 MHz ultrasonic transducer, analog Doppler unit (Toshiba 140A color Doppler ultrasonography), recorder (Sony), analog/digital interface board

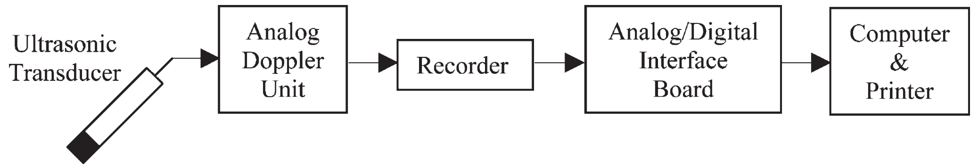

Fig. 1. Block diagram of measurement system.

(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. The internal carotid arterial Doppler signals were sampled in 5 kHz and framed by equal time intervals. The frame length was chosen as 128.

2.3. Lyapunov exponents

Lyapunov exponents are a quantitative measure for distinguishing among the various types of orbits based upon their sensitive dependence on the initial conditions, and are used to determine the stability of any steady-state behavior, including chaotic solutions. The reason why chaotic systems show aperiodic dynamics is that, phase space trajectories that have nearly identical initial states will separate from each other at an exponentially increasing rate captured by the so-called Lyapunov exponent [12–15]. This is defined as follows. Consider two (usually the nearest) neighboring points in phase space at time 0 and at time t, distances of the points in the ith direction being $\|\delta x_i(0)\|$ and $\|\delta x_i(t)\|$, respectively. The Lyapunov exponent is then defined by the average growth rate λ_i of the initial distance,

$$\frac{\|\delta x_i(t)\|}{\|\delta x_i(0)\|} = 2^{\lambda_i t}(t \to \infty) \quad \text{or}$$

$$\lambda_i = \lim_{t\to\infty} \frac{1}{t}\log_2 \frac{\|\delta x_i(t)\|}{\|\delta x_i(0)\|}. \tag{1}$$

The existence of a positive Lyapunov exponent indicates chaos [12–15]. This shows that any neighboring points with infinitesimal differences at the initial state abruptly separate from each other in the ith direction. In other words, even if the initial states are close, the final states are much different. This phenomenon is sometimes called sensitive dependence on initial conditions. Numerous methods for calculating the Lyapunov exponents have been developed during the past decade [16]. Generally, the Lyapunov exponents can be estimated either from the equations of motion of the dynamic system (if it is known) [17], or from the observed time series [18]. The latter is what is of interest due to its direct relation to the work in this paper. The idea is based on the well-known technique of state space reconstruction with delay coordinates to build a system with Lyapunov exponents identical to that of the original system from which our measurements have been observed. Generally, Lyapunov exponents can be extracted from observed signals in two different ways. The first is based on the idea of following the time-evolution of nearby points in the state space [19]. This method provides an estimation of the largest Lyapunov exponent only. The second method is based on the estimation of local Jacobi matrices [20] and is capable of estimating all the Lyapunov exponents. Vectors of all the Lyapunov exponents for particular systems are often called their Lyapunov spectra.

2.4. Artificial neural networks

The MLPNNs, which have features such as the ability to learn and generalize, smaller training set requirements, fast operation, ease of implementation and, therefore, most commonly used neural network architectures, have been adapted for detection of internal carotid artery stenosis and occlusion.

2.4.1. Multilayer perceptron neural networks

The MLPNN is a nonparametric technique for performing a wide variety of detection and estimation tasks [21–23]. Training process is an important characteristic of the artificial neural networks (ANNs), whereby representative examples of the knowledge are iteratively presented to the network, so that it can integrate this knowledge within its structure. There are a number of training algorithms used to train an MLPNN and a frequently used one is called the backpropagation training algorithm [21–23]. The backpropagation algorithm, which is based on searching an error surface using gradient descent for points with minimum error, is relatively easy to implement. However, backpropagation has some problems for many applications. The algorithm is not guaranteed to find the global minimum of the error function since gradient descent may get stuck in local minima, where it may remain indefinitely. In addition to this, long training sessions are often required in order to find an acceptable weight solution because of the well-known difficulties inherent in gradient descent optimization. Therefore, a lot of variations to improve the convergence of the backpropagation were proposed. Optimization methods such as second-order methods (conjugate gradient, quasi-Newton, Levenberg–Marquardt) have also been used for ANN training in recent years. The Levenberg–Marquardt algorithm combines the best features of the Gauss–Newton technique and the steepest-descent algorithm, but avoids many of their limitations. In particular, it generally does not suffer from the problem of slow convergence [24,25]. Therefore, in this study, the MLPNN was trained with the Levenberg–Marquardt algorithm.

2.4.2. *Levenberg–Marquardt algorithm*

ANN training is usually formulated as a nonlinear least-squares problem. Essentially, the Levenberg–Marquardt algorithm is a least-squares estimation algorithm based on the maximum neighborhood idea. Let $E(\mathbf{w})$ be an objective error function made up of m individual error terms $e_i^2(\mathbf{w})$ as follows:

$$E(\mathbf{w}) = \sum_{i=1}^{m} e_i^2(\mathbf{w}) = \|f(\mathbf{w})\|^2, \tag{2}$$

where $e_i^2(\mathbf{w}) = (\mathbf{y}_{di} - \mathbf{y}_i)^2$ and $\mathbf{y}_{di}$ is the desired value of output neuron i, $\mathbf{y}_i$ is the actual output of that neuron.

It is assumed that function $f(\cdot)$ and its Jacobian J are known at point $\mathbf{w}$. The aim of the Levenberg–Marquardt algorithm is to compute the weight vector $\mathbf{w}$ such that $E(\mathbf{w})$ is minimum. Using the Levenberg–Marquardt algorithm, a new weight vector $\mathbf{w}_{k+1}$ can be obtained from the previous weight vector $\mathbf{w}_k$ as follows:

$$\mathbf{w}_{k+1} = \mathbf{w}_k + \delta\mathbf{w}_k, \tag{3}$$

where $\delta\mathbf{w}_k$ is defined as

$$\delta\mathbf{w}_k = -\left(J_k^{\mathrm{T}} f(\mathbf{w}_k)\right)\left(J_k^{\mathrm{T}} J_k + \gamma\mathbf{I}\right)^{-1}. \tag{4}$$

In Eq. (4), J_k is the Jacobian of f evaluated at $\mathbf{w}_k$, γ is the Marquardt parameter, and $\mathbf{I}$ is the identity matrix [24,25].

3. Results and discussion

3.1. *Feature extraction by computing Lyapunov exponents*

In the present study, the technique used in the computation of Lyapunov exponents was related with the Jacobi-based algorithms. The Lyapunov exponents of the internal carotid arterial Doppler signals obtained from a healthy subject (subject no: 15), a subject suffering from internal carotid artery stenosis (subject no: 32), and a subject suffering from internal carotid artery occlusion (subject no: 43) are given in Fig. 2. It can be noted that the Lyapunov exponents of the internal carotid arterial Doppler signals obtained from a healthy subject, a subject suffering from internal carotid artery stenosis, and a subject suffering from internal carotid artery occlusion are different from each other. As it is seen from Fig. 2, there are positive Lyapunov exponents, which confirm the chaotic nature of the internal carotid arterial Doppler signals obtained from healthy subjects, subjects suffering from internal carotid artery stenosis and subjects suffering from internal carotid artery occlusion. The largest Lyapunov exponents of the internal carotid arterial Doppler signals obtained from 60 different subjects belonging to three classes (20 healthy subjects, 20 subjects suffering from internal carotid artery stenosis, 20 subjects suffering from internal carotid artery occlusion) are shown in Fig. 3. From Fig. 3 one can see that there is a significant increase in the largest Lyapunov exponent values of the internal carotid arterial Doppler signals obtained

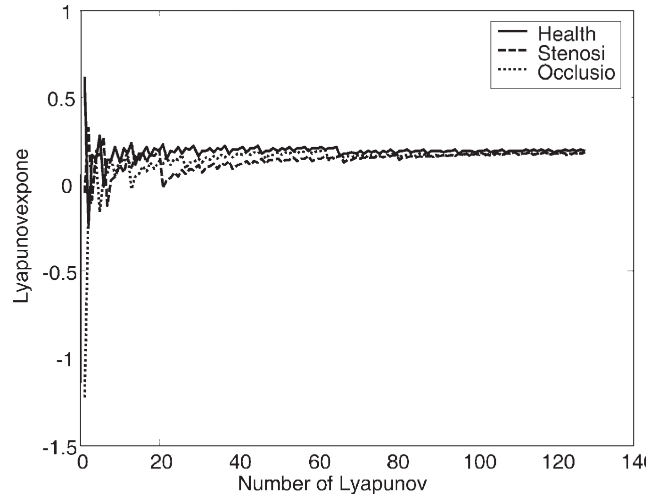

Fig. 2. Lyapunov exponents of the internal carotid arterial Doppler signals obtained from: a healthy subject (subject no: 15); a subject suffering from internal carotid artery stenosis (subject no: 32); a subject suffering from internal carotid artery occlusion (subject no: 43).

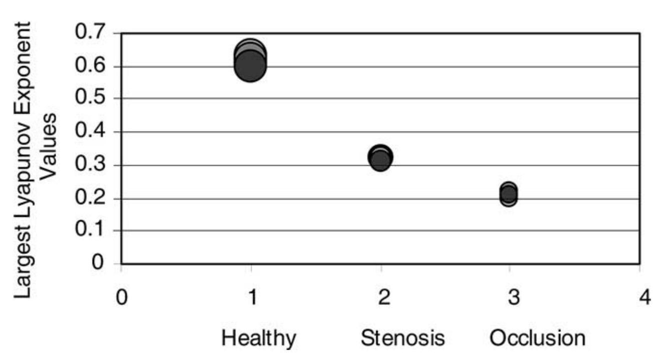

Fig. 3. Largest Lyapunov exponent values of the internal carotid arterial Doppler signals obtained from 60 different subjects belonging to three classes (20 healthy subjects, 20 subjects suffering from stenosis, 20 subjects suffering from occlusion).

from healthy subjects comparing with the largest Lyapunov exponent values of the internal carotid arterial Doppler signals obtained from subjects suffering from stenosis and occlusion. Moreover, the largest Lyapunov exponent values of internal carotid arterial Doppler signals obtained from subjects suffering from stenosis are higher than that of internal carotid arterial Doppler signals obtained from subjects suffering from occlusion. The Lyapunov exponents were computed using MATLAB software package.

3.2. Application of MLPNN to internal carotid arterial Doppler signals

ANN architectures are derived by trial and error and the complexity of the neural network is characterized by the number of hidden layers. There is no general rule for selection of appropriate number of hidden layers. A neural network with a small number of neurons may not be sufficiently powerful to model a complex function. On the other hand, a neural network with too many neurons may lead to overfitting the training sets and lose its ability to generalize, which is the main desired characteristic of a neural network. The most popular approach to finding the optimal number of hidden layers is by trial and error. In the present study, after several trials it was seen that two hidden layered network achieved the task in high accuracy. The most suitable network configuration found was 10 neurons for each hidden layer. In the hidden layers and the output layer, sigmoidal function was used, which introduced two important properties. First, the sigmoid is nonlinear, allowing the network to perform complex mappings of input to output vector spaces, and second, it is continuous and differentiable, which allows the gradient of the error to be used in updating the weights. The MLPNN was trained by using the Levenberg–Marquardt algorithm. For the Levenberg–Marquardt algorithm, the Marquardt parameter (γ) was set to 0.01. The MLPNN was implemented by using MATLAB software package (MATLAB version 6.0 with neural networks toolbox).

Selection of the ANN inputs is the most important component of designing the neural network 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 Lyapunov exponents contain a significant amount of information about the Doppler signal, the computed Lyapunov exponents of the internal carotid arterial Doppler signals were used as the MLPNN inputs. For each internal carotid arterial Doppler signal frame (128 samples), 128 Lyapunov exponents were computed.

The adequate functioning of ANN depends on the sizes of the training set and test set. In this study, 60 of 160 subjects were used for training and the rest for testing. A practical way to find a point of better generalization is to use a small percentage (around 20%) of the training set for cross validation. For obtaining a better network generalization 12 training subjects were selected randomly to be used as a cross validation set. The training set consisted of 20 subjects suffering from internal carotid artery stenosis, 20 subjects suffering from internal carotid artery occlusion, and 20 healthy subjects. The testing set consisted of 39 subjects suffering from internal carotid artery stenosis, 33 subjects suffering from internal carotid artery occlusion, and 28 healthy subjects. The cross validation set consisted of four subjects suffering from internal carotid artery stenosis, four subjects suffering from internal carotid artery occlusion, and four healthy subjects.

The outputs of the MLPNN were represented by unit basis vectors:

$[0\ 0\ 1]$ = healthy
$[0\ 1\ 0]$ = internal carotid artery stenosis
$[1\ 0\ 0]$ = internal carotid artery occlusion

3.3. Performance analysis of MLPNN

The MLPNN was trained with the training set, cross validated with the cross validation set, and checked with the test set. In this study, performance analysis of the MLPNN is examined in two parts: training performance and testing performance.

3.3.1. Training performance of MLPNN

The training set provided to the MLPNN was representative of the whole space of concern so that the trained MLPNN had the ability of generalization. In training, a representative training set with examples was presented iteratively to the MLPNN and the output activations were calculated using the MLPNN weights. An error term, based on the difference between the output of MLPNN and desired output, was then propagated back through the MLPNN to calculate changes of the interconnection weights. The square difference between the output of MLPNN and the desired output over training iterations was plotted for observing how well the MLPNN was trained. The curve of the mean square error (MSE) versus iteration is the training curve. In general, it is known that a network with enough weights will always learn the training set better as the number of iterations is increased. However, this decrease in the training set error is not always coupled to better performance in the test. When the network is trained too much, the network memorizes the training patterns and does not generalize well. The training holds the key to an accurate solution, so the criterion to stop training must be very

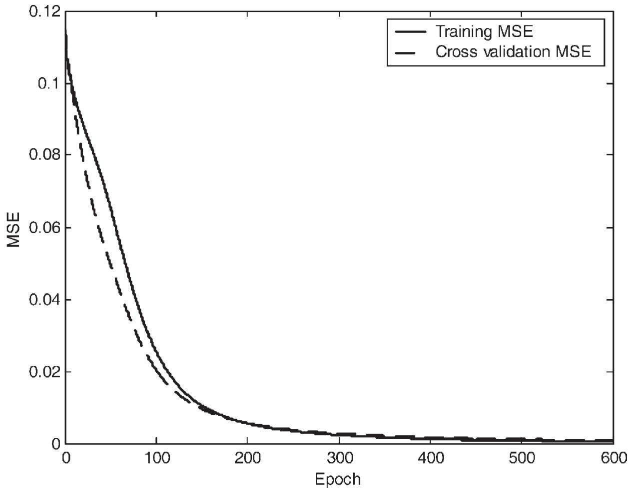

Fig. 4. Training and cross validation MSE curves of the MLPNN.

well described. Cross validation is a highly recommended criterion for stopping the training of a network. When the error in the cross validation increases, the training should be stopped because the point of best generalization has been reached. In Fig. 4, the error in training set and the cross validation set is shown on the same graph. The values of minimum MSE and final MSE during training and cross validation are given in Table 1. In this study, as it is seen from Table 1, training was done in 600 epochs since the cross validation error began to rise at 600 epochs. Since MSE (Fig. 4) converged to a small constant approximately zero in 600 epochs, the MLPNN trained with the Levenberg–Marquardt algorithm was determined to be successful.

3.3.2. Testing performance of MLPNN

After a training phase for testing the MLPNN, 100 test data that the network had not seen before were applied to the network. The MLPNN applied its past experience to test data and produced a solution based on the training and topology of the MLPNN. The evaluation of testing performance of the MLPNN was performed by assessment of classification results, the values of statistical parameters, receiver operating characteristic (ROC) curve analysis, and performance evaluation parameters.

Table 1
The values of minimum and final MSE during training and cross validation

Network	Training	Cross validation
Number of epochs	600	600
Minimum MSE	0.000520	0.000834
Final MSE	0.000520	0.000834

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 study, there were three classes: healthy, internal carotid artery stenosis, and internal carotid artery occlusion. Classification results of the MLPNN were displayed by a confusion matrix. The confusion matrix showing the classification results of the MLPNN is given below.

Confusion matrix showing the classification results of the MLPNN

Output/desired	Healthy	Internal carotid artery stenosis	Internal carotid artery occlusion
Healthy	27	1	0
Internal carotid artery stenosis	1	37	1
Internal carotid artery occlusion	0	1	32

According to the confusion matrix, one healthy subject was classified incorrectly by the MLPNN as a subject suffering from internal carotid artery stenosis, one subject suffering from internal carotid artery stenosis was classified as a healthy subject, one subject suffering from internal carotid artery stenosis was classified as a subject suffering from internal carotid artery occlusion, and one subject suffering from internal carotid artery occlusion was classified as a subject suffering from internal carotid artery stenosis.

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

Specificity: number of correctly classified healthy subjects/number of total healthy subjects.
Sensitivity (*internal carotid artery stenosis*): number of correctly classified subjects suffering from stenosis/number of total subjects suffering from stenosis.
Sensitivity (*internal carotid artery occlusion*): number of correctly classified subjects suffering from occlusion/number of total subjects suffering from occlusion.
Total classification accuracy: number of correctly 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 MLPNN classified healthy subjects, subjects suffering from internal carotid artery stenosis, and subjects suffering from internal carotid artery occlusion with the accuracy of

Table 2
The values of statistical parameters

Statistical parameters	Values (%)
Specificity	96.43
Sensitivity (internal carotid artery stenosis)	94.87
Sensitivity (internal carotid artery occlusion)	96.97
Total classification accuracy	96.00

96.43%, 94.87%, and 96.97%, respectively. The healthy subjects, subjects suffering from internal carotid artery stenosis, and subjects suffering from internal carotid artery occlusion were classified with the accuracy of 96.00%.

As a second experiment, the first 80 Lyapunov exponents were used as the MLPNN inputs since a redundancy was observed in the Lyapunov exponents about 80 (Fig. 2). Then the MLPNN classified healthy subjects, subjects suffering from internal carotid artery stenosis, and subjects suffering from internal carotid artery occlusion with the accuracy of 96.43%, 97.44%, and 96.97%, respectively. The healthy subjects, subjects suffering from internal carotid artery stenosis, and subjects suffering from internal carotid artery occlusion were classified with the accuracy of 97.00%. From these values one can see that the MLPNN performance improve slightly.

The performance of a test can be evaluated by plotting a ROC curve for the test. For a given result obtained by a classifier system, four possible alternatives exist that describe the nature of the result: (i) true positive (TP), (ii) false positive (FP), (iii) true negative (TN), and (iv) false negative (FN) [26]. In this study, a TP decision occurred when the positive detection of the MLPNN coincided with a positive detection of the physician. An FP decision occurred when the MLPNN made a positive detection that did not agree with the physician. A TN decision occurred when both the MLPNN and the physician suggested the absence of a positive detection. An FN decision occurred when the MLPNN made a negative detection that did not agree with the physician. A good test (curve in Fig. 5) is one for which sensitivity rises rapidly and 1-specificity hardly increases at all until sensitivity becomes high. ROC curve which is shown in Fig. 5 represents the MLPNN performance on the test file.

The difference between the output of the network and the desired response is referred to as the error and can be measured in different ways. In this study, MSE, mean absolute error (MAE), minimum absolute error, maximum absolute error, and correlation coefficient (r) were used for measuring error of the MLPNN. The sizes of MSE and MAE can be used to determine how well the network output fits the desired output, but they may not reflect whether the two sets of data move in the same direction. The correlation coefficient solves this problem. The correlation coefficient is limited within the range [−1,1]. When $r = 1$ there is a perfect positive linear correlation between network output and desired output, which means that they vary by the same amount. When $r = -1$ there is a perfectly linear negative correlation between network output and desired output, that means they vary in opposite ways. When $r = 0$ there is no correlation between network output and desired output. Intermediate values describe partial correlations. The values of performance evaluation parameters of the presented MLPNN are given for healthy subjects, subjects suffering from internal carotid artery stenosis and subjects suffering from internal carotid artery occlusion in Table 3. The classification results, the values of statistical parameters, ROC curve, and performance evaluation parameters indicated that testing of the MLPNN trained with the Levenberg–Marquardt algorithm was successful.

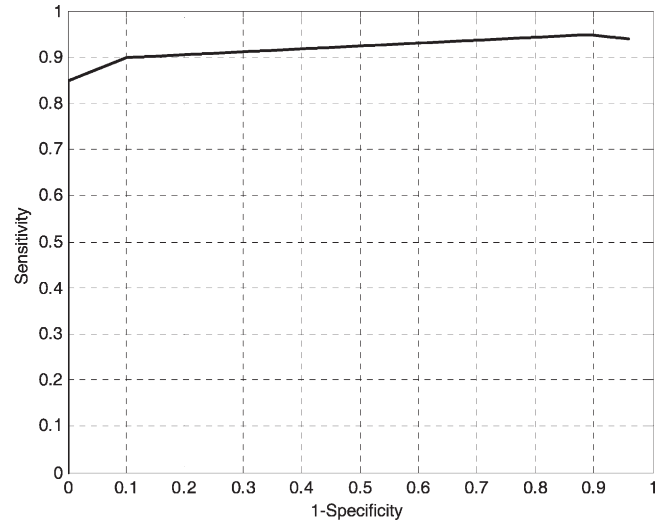

Fig. 5. ROC curve.

Table 3
The values of performance evaluation parameters during test process

Performance	Result (healthy)	Result (internal carotid artery stenosis)	Result (internal carotid artery occlusion)
MSE	0.000261	0.000614	0.000147
MAE	0.015622	0.019612	0.014512
Minimum absolute error	0.006103	0.008521	0.004789
Maximum absolute error	0.123125	0.176123	0.116195
r	0.979985	0.956647	0.987493

4. Conclusion

This paper presented a new application of detecting variabilities such as stenosis and occlusion in the physical state of internal carotid arterial Doppler signals using Lyapunov exponents. Toward achieving this aim, the internal carotid arterial Doppler signals were considered as chaotic signals and this consideration was tested successfully using the nonlinear dynamics tools in the literature, like the state space reconstruction and the computation of Lyapunov exponents. In state space reconstruction, the problem was turned out to be how could the time delay and the embedding dimension be selected. Therefore, the computation of Lyapunov exponents was taken as the basis for the automatic detection of internal carotid artery stenosis and occlusion in the present study. More specifically, the internal carotid arterial Doppler signals were modelled using an MLPNN. The classification results, the values of statistical parameters, ROC curve, and performance evaluation parameters were used for evaluating the classifier. The MLPNN trained with the Levenberg–Marquardt algorithm was used to detect stenosis and occlusion in internal carotid arteries. The MLPNN was trained, cross validated and tested with the 128 Lyapunov exponents of the internal carotid arterial Doppler signals obtained from healthy subjects, subjects suffering from internal carotid artery stenosis and subjects suffering from internal carotid artery occlusion. The healthy subjects, subjects suffering from internal carotid artery stenosis, and subjects suffering from internal carotid artery occlusion were classified with the accuracy of 96.00%. As a second experiment, the first 80 Lyapunov exponents were used as the MLPNN inputs since a redundancy was observed in the Lyapunov exponents about 80. Then the MLPNN classified the healthy subjects, subjects suffering from internal carotid artery stenosis, and subjects suffering from internal carotid artery occlusion with the accuracy of 97.00%. The MLPNN performance improved slightly when the dimensionality of the extracted feature vectors was reduced. We, therefore, have concluded that the proposed classifier can be used in detecting stenosis and occlusion in internal carotid arteries.

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