DETECTION OF ATHEROSCLEROSIS IN EARLY PHASE USING POWER SPECTRAL DENSITIES OF CAROTID ARTERY DOPPLER SIGNALS

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Abstract: This study investigates the early phase of atherosclerosis from carotid artery Doppler signals. The variations in the sahape of the power spectral densities (PSD) of Doppler signals were examined in order to medical information. PSD is acquired with Autoregressive (AR) modeling at a nonstenotic arterial site in patients with early phase of atherosclerosis and healthy volunteers. Global performance of the proposed method was evaluated by means of Artificial Neural Networks (ANN) instead of visual inspection of PSD. The overall results show that 98.1% correct classification was achieved, whereas 1 false classification has been observed for the group of 57 people for testing in total. With these results (the values of statistical parameters), this network has about 96% sensivity, 100% specivity and avaraged detection ratio is calculated to be 98%. The benefit of the system is to assist the physician to make the final decision about existing of diseases without hesitation.

Introduction

Atherosclerosis, commonly referred to as hardening of the arteries is the build up of fatty materials (plaque) on the inside of the arteries. Gradually, the inner surface of arteries can be made rough by fatty deposits or plaques and blood flow through them can become reduced [1,2]. The narrowing and hardening of the arteries has dramatic effects on blood pressure, resistance and blood flow. Resistance increases when radius decreases, as friction of blood flow against vessel wall increases. Therefore the circulation of blood flow is reduced.

When atherosclerosis develops in the arteries that supply the brain (carotid arteries), a stroke may occur; when it develops in the arteries that supply the heart (coronary arteries), a heart attack may occur [3,4].

There are a number of tests that of atherosclerosis, including blood tests, coronary angiography and ultrasound. Invasive, sophisticated clinical measurements have provided data from recordings of arterial blood flow, pressure, and diameter changes. When the symptoms develop, catheter angiography is considered as the gold standard to detect and quantify the stenosis. Since angiography is invasive and has a relatively high cost, noninvasive ultrasonic Doppler sonography is generally recommended. Recent advances in the Doppler imaging technique have made possible evaluation of the temporal and spatial flow characteristics in the different portions of the arterial system, such as aorta, coronary, carotid and peripheral arteries. The analysis of Doppler signals provide information about physiology and pathology, through applications such as flow measurement and the detection of significant changes in "Doppler waveform" shape [5].

It is often useful to to analyze the spectrum of the Doppler-shifted signal to assess the degree of a disease [6]. The use of spectrum analysis to display Doppler frequency shift signals provides not only the best means of measuring blood flow velocity but also information about the presence of disturbed flow [7]. The Doppler power spectral density (PSD) describes how the power (or variance) of a time series is distributed with frequency and thus spectral analysis of the Doppler signal produces information concerning the velocity distribution in the artery [6,7].

Artificial Neural Networks have been used widely in many application areas in recent years . Applications of ANNs in the medical field include phtoelectric plethysmography pulse waveform analysis, diagnosis of myocardial infarction, electrocardiogram analysis and differantation of assorted pathological data. However, to date, neural network analysis of Doppler signals is a relatively new approach [8,9].

In this study, we have employed the PSD using Autoregressive (AR) modeling, and ANN in order to distinguish between patients in the early phase of atherosclerosis and healthy subjects [10].

The aim of this study is apply and evaluate of PSD of carotid artery Doppler signals to ANN. We have implemented an ANN that will not only simplify the diagnosis but also enable the physician to make a quicker judgement about the beginning of disease more confidencely.

Materials and Methods

2.1 Hardware and Demographic Acknowledgments

Carotid arterial Doppler ultrasound signals were acquired from left carotid arteries of 47 patients and 60 healthy volunteers. The subjects had no clinical and echocardiographic evidence of valvular disease or heart failure. The patient group included 26 males and 21 females with an established diagnosis of the early phase of atherosclerosis through coronary or aortofemoropopliteal (lower extremity) angiographies (mean age, 47 years; range, 35-62 years). Healthy volunteers were young non-smokers who seem to not

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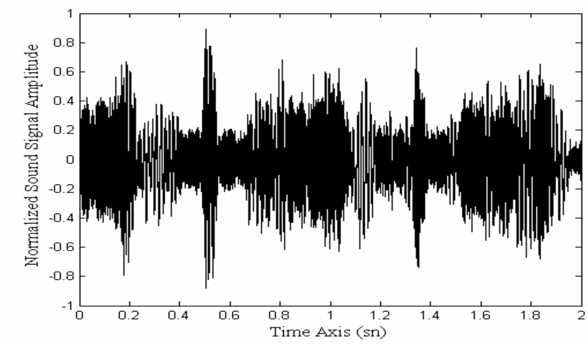
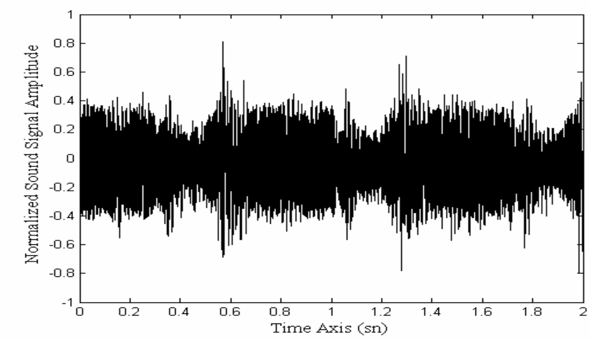
bear any risk of atherosclerosis, including 34 males and 26 females (mean age, 31 years; range, 19-46 years).

Doppler signal acquisition was conducted by Toshiba PowerVision 6000 Doppler ultrasound unit in the radiology departments of Erciyes university hospital and Dinar state hospital. The system hardware was composed of Digital Doppler ultrasound unit that can work in the pulsed mode, linear ultrasound probe, input-output card and a personal computer [11]. Before the data was recorded, a color and pulsed Doppler ultrasound examination of the left carotid artery was performed in order to exclude the presence of a hemodynamically significant stenosis. A linear ultrasound probe of 10 MHz was used to transmit pulsed ultrasound signals to the proximal left carotid artery. Signals reflected from the artery were recorded to derive out the Doppler shift frequencies as seen in Figure 1. In all tests performed on the patients and healthy subjects, the insonation angle and the presetting of the ultrasound were kept constant. The audio output of ultrasound unit was sampled at 44100 Hz and then sent to a PC via an input-output card [11].



(a)



(b)

Figure 1: Carotid arterial Doppler data acquired from a healthy (a) and a patient with atherosclerosis subject (b).

2.2 Spectral Analysis of Doppler signals

Doppler shift frequency, which is directly proportional to the blood flow speed, is subjected to spectral analysis [12].

In the present study, power spectral density is acquired with AR-Burg processing of the Doppler signals at a nonstenotic arterial site in patients with early phase of atherosclerosis and healthy volunteers. Among several methods of estimation of the AR model parameters (Yule Walker equation, Burg algoritm, least squares algorithm), in this study, the Burg method for estimating the AR parameters are used (Figure 2). Since AR-Burg method is computationally efficient and yields stable estimates, PSD estimates of carotid arterial Doppler signals are obtained by using this method. The AR-Burg method is based on the minimization of the forward and backward prediction errors and estimation of the reflection coefficient. Acquired Doppler data was grouped in frames of 256 data points and we have utilized PSD using AR-Burg method on these frames.

2.2.1 AR - Burg Method for spectral analysis

Autoregressive model is suitable for representing spectra with narrow peaks and second a number of linear equations need to be solved for finding the AR parameters. The Burg method is a least-squares optimization problem with the constraint that the reflection coefficients obtained from the problem must satisfy Levinson-Durbin recursion, i.e. The Burg method has three advantages; 1)It has high frequency resolution, 2)It results stable AR model, 3)Because it uses Levinson-Durbin recursion [13]. The model based (parametric) methods are based on modeling the data sequence x(n) as the output of linear system characterized by a rational system. In the model based methods, the spectrum estimations procedure consists of two steps. The parameters of the are estimated from given data sequences x(n), $0 \leq n \leq N-1$. Then from these estimates, the PSD estimate is computed. In AR method, data can be modeled as output of a casual, all-pole, discrete filter, whose input is white noise. The AR method of order p is expressed following equation:

$$x(n) = -\sum a(k)x(n-k) + w(n) \qquad (1)$$

where a(k) are the AR coefficients w(n) is white noise of variance equal to σ^2. The AR(p) model can be characterized by the AR parameters $\{a[1], a[2], \ldots, a[p], \sigma^2\}$. The power spectrum density (PSD) is

$$P_{AR}(f) = \frac{\sigma^2}{|A(f)|^2} \qquad (2)$$

$$A(f) = 1 + a_1 e^{-j2\pi f} + \ldots\ldots + a_p e^{-j2\pi fp} \qquad (3)$$

Selection of the model order was based an examination of the consistency of several order determination methods under noise free conditions for each of the analyzed data length realizations. Akaike's final prediction error yielded curves that asymptotically approached a minimum with knee around p=25 [13, 14].

2.3 Artificial Neural Networks

An ANN is a nonlinear processing system where information spreads parallel on. An ANN can determine its conditions and adjust itself to provide different responses by using inputs and desired outputs, which are provided to the system. ANN is trained with the available data samples to explore the relation between inputs and outputs, so that you can reach the proper and accurate outputs when you input some new data [15].

In this study a Multilayer feed forward ANN was implemented in the SAS software package (SAS 9.1.2 Windows). This choice is appropriate for solving pattern classification problems where supervised learning is implemented with a Levenberg Marquard **(**LM) backpropagation algorithm. A LM back propagation neural network was used for the interpretation of power spectral density estimates . The advantage of using this type of ANN is the rapid execution of the trained network, which is particularly advantageous in signal processing applications. ANN training is usually formulated as a nonlinear least-squares problem.

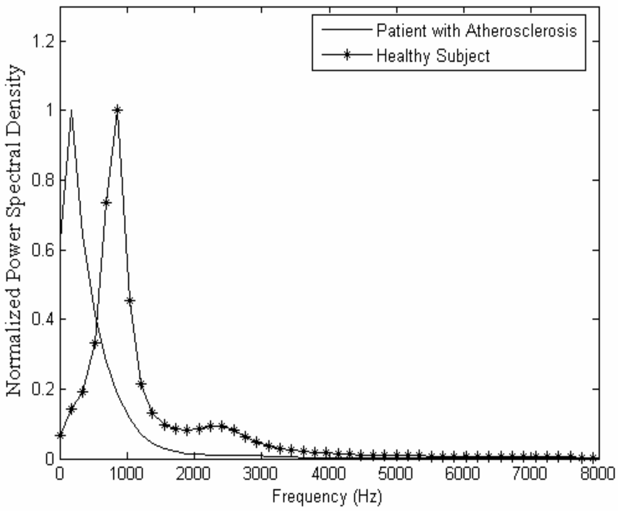


Figure 2: AR power spectral density distribution of a patient with atherosclerosis and a healthy subject.

2.3.1 LM Algorithm

The backpropagation algorithm is a widely used training procedure that adjusts the connection weights of a Multi Layer Perceptron (MLP) [16]. Essentially, the LM algorithm is a least–squares estimation algorithm based on the maximum neighborhood idea. A MLP consists of three layers: an input layer, an output layer, and one or more hidden layers. Each layer is composed of a predefined number of neurons. The neurons in the input layer only act as buffers for distributing the input signals x_i to neurons in the hidden layer. Each neuron *j* in the hidden layer sums up its input signals x_i after weighting them with the strengths of the respective connections w_{ij} from the input layer, and computes its output y_j as a function *f* of the sum:

$$\mathbf{y}_j = f(\sum \mathbf{w}_{ij}\mathbf{x}_i) \quad (4)$$

where *f* is the activation function that is necessary to transform the weighted sum of all signals impinging onto a neuron.. The activation function *f* can be a simple threshold function, a sigmoidal, hyperbolic tangent, or radial basis function. The output of neurons in the output layer is similarly computed [17].

Training a network consists of adjusting the network weights using the different learning algorithms. A learning algorithm gives the change $\Delta w_{ij}(t)$ in the weight of a connection between neurons *i* and *j* at time *t*. For the Levenberg-Marquardt learning algorithm, the weights are updated according to the following formula

$$\mathbf{w}_{ij}(t+1) = \mathbf{w}_{ij}(t) + \Delta\mathbf{w}_{ij}(t) \quad (5)$$

with

$$\Delta\mathbf{w}_{ij} = \left[\mathbf{J}^T(w)\mathbf{J}(w) + \mu\mathbf{I}\right]^{-1}\mathbf{J}^T(w)E(w) \quad (6)$$

where $\boldsymbol{J}$ is the Jacobian matrix, μ is a constant, $\boldsymbol{I}$ is a identity matrix, and *E(w)* is an error function [18].

ANN underwent supervised learning to perform successful pattern recognition of the carotid artery Doppler signals. During supervised learning, the ANN was trained on input vectors and the target output vectors with which it is required to associate the input vectors. With sufficient training, the ANN should be able to classify correctly previously unseen input vectors. The network is iterated for single and double hidden layers with combinations of one to twenty neurons in each layer. For each layer combination, the target mean square error was set to $0.1*10^{-5}$ and the epoch number was taken as 20.

The train input data set consisted of 30 normal and 23 patients, while the test data set was made of 30 normal and 24 patients. The minimum training and testing errors were accomplished with the combination of two hidden layer consisting of 8-3 neurons. Hidden layer sigmoidal function and output layer linear function was used. The training parameters and structure of the MLP used in this study are as shown in Table 1.

The performance of the ANN algorithms were assessed by the following measures as seen Table 2 [19]. For a given decision suggested by a certain output neuron four possible alternatives exist; true positive (TP), false positive (FP), true negative (TN), and false negative (FN). In our study TP decision occurs when the positive diagnosis of the system coincides with a positive diagnosis according to the physician. An FP decision occurs when the system made a positive diagnosis that does not agree with the physician. A TN decision occurs when both the system and physician suggest the absence of a positive diagnosis. An FN decision occurs when the system when the system made a negative diagnosis that does not agree with the physician. [20].

*Sensitivity (SEN)***:** A measure of the ability of the classifier to detect atherosclerosis.

Sensitivity = (TP)/(TP+FN) %

Specificity (SPE): A measure of the ability of the classifier to specify normal.

Specificity = TN/(TN+FP) %

Average Detection Rate (ADR): The average of sensitivity and specificity.

Average Detection Rate (ADR)= (Sensitivity+Specificity)/2 %.

Table 1: ANN architecture and training parameters

ARCHITECTURE		TRAINING PARAMETERS	
The number of layers	4	**Training Algorithm**	LM
The number of neuron on the layers	Input : 45 Hidden : 8-3 Output : 1	**Mean-square error**	$8.29*10^{-6}$
		Mean absolute error	0.0026
Activation Functions	Tan-sigmoid	**Epoch number**	6

Table 2: Test results

GROUP TYPE	REAL NUMBER OF SUBJECTS IN THE TEST GROUP	TRUE	FALSE
Negative (Normal)	30	29(%96.7)	1(%3.3)
Positive (Subnormal)	24	24(%100)	0(%0)
TOTAL	54	53(%97)	1 (%3)
Sensitivity (SEN) = %96			
Specifity (SPE) = %100			
Average Detection Rate (ADR).= %98			

Results and Discussion

Doppler signals reflected from the carotid artery recorded in the time domain have not extra information about existence of the diseases (Figure 1). Therefore these signals were analysed in the frequency domain to reveal differencies between healthy and patient in the beginning of atherosclerosis. To assess the spectral analysis, we have employed PSD from the carotid artery Doppler shift signals as seen Figure 2. In recent years, in the clinics the physcians prefer using the sonogram to diagnose the atherosclerosis. The Doppler sonograms describe how the power of a time series is distributed with frequency. But sometimes the fuzzy appearance of the sonograms makes physicians suspicious about the existence of diseases and causes false diagnosis. Our technique gets around this problem using ANN to decide and assist the physician to make the final judgment in confidence. AR method of preprocessing was used the extract the PSD. After that first 45 data point of the logarithm of the values of PSD belongs to each subjects was used as input of ANN (Figure 3). These 45 sample represent %99 of sum of PSD.

After the training phase, testing of the LM backpropagation neural network was established. The data, which has not been used as an input to the network, was applied to the network for testing the network performance. After the process, normal (healthy) subjects are classified correctly with 96.7% and incorrectly with 3.3% (Table 2). Subjects having atherosclerosis are classified correctly with 100%. In this case, by using this network classification, normal subjects and patient subjects are classified with 98% ADR.

The sizes of mean square error (MSE) and mean absolute error (MAE) can be used to determine how well the network output fits desired output, a testing MSE of $1.3*10^{-5}$ and MAE of 0.0021 was observed for our optimized MLP feed forward network with a training MSE of $8.29*10^{-6}$ (Figure 4) and MAE of 0.0026. As seen in Table 2, 98.1% success rate of classification was accomplished with the designed feature extraction and the neural network structures. Final results were classified as normal and subnormal. There was one false classification in the negative group, while 29 subjects were correctly recognized as healthy. In the positive (patient) group, any subjects were misclassified, and 24 people were accurately classified as diseased. The overall results, shows that 98.1% correct classification was achieved, whereas 1 false classifications have been observed for the group of 57 people for testing in total. With these results, this network has about 96% SEN, 100% SPE and ADR is calculated to be 98% (Table 2).

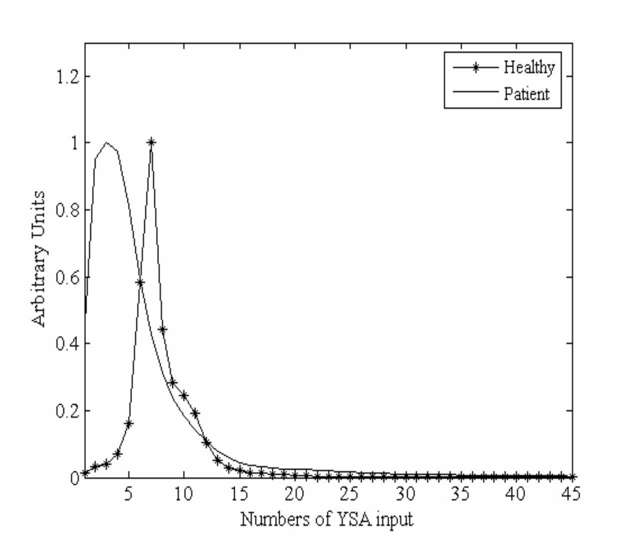


Figure 3: Power spectral densities used as input of the ANN of healthy (Subject No:13) and patient with atherosclerosis (Subject No:24)

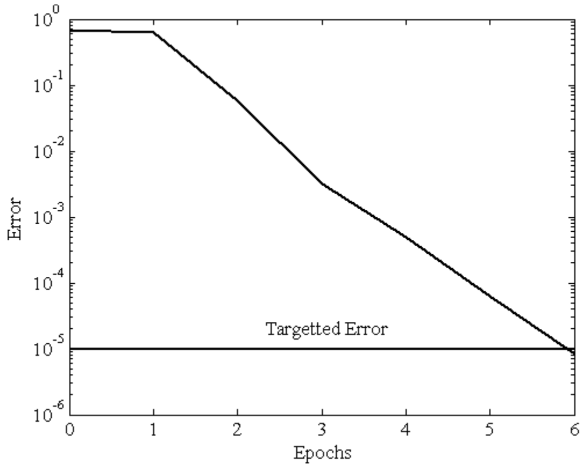


Figure 4: Variation of the error rate with respect to the epoch number in the ANN

These results shown that ANN classified Doppler signals succesfully. However, training time and processing complexity were reduced using PSD-ANN architecture. Although our expert diagnosis system was carried out on the carotid artery, similar results for the other arteries and the other Doppler studies can be expected.

The limitation of our system is to be off line. But for a possible extension of the available system to real signal anaysis, of course, this limitation will have to be ovecome.

Conclusions

ANN is a valuable tool in the medical field for the devolopment of desicion support system. The utilty of the MLP has been demonstrated when used as a classifier for carotid artery Doppler signals. We are proposing a complimentary system that can be coupled to software of the ultrasonic Doppler devices. The benefit of the system is to assist the physician to make the final decision about existing of diseases without hesitation. The diagnosis performances of this study show the advantages of this system: it is rapid, easy to operate, non invasive and inexpensive. This system is of the better clinical application over others, especially for earlier survey of population.

References

[1] HIRAI T., SASAYAMA S., KAWASAKI T., YAGI S., (1989): ‘Stiffness of systemic arteries in patients with myocardial infarction. A noninvasive method to predict severity of coronary atherosclerosis' (Circulation), pp.78 –86

[2] STEFANADIS C., STRATOS C., BOUDOULAS H., KOUROUKLIS C., TOUTOUZAS P., (1990), 'Distensibility of the ascending aorta, comparison of invasive and non-invasive techniques in healthy men and in men with coronary artery disease', (Eur Heart J), pp. 990 –996

[3] HOSKINS P.R., MCDICKEN W.N., ALLAN V., (2000) 'Haemodynamics and blood flow', In: Allan PL, DUBBINS PA, POZNIAK MA, MCDICKEN WN. (Ed.), (Clinical Doppler Ultrasound. London: Churchill Livingstone), pp. 27-38.

[4] SCHOEN F.J.; COTRAN R.S., (1999) ‘Blood vessels Pathologic basis of disease' (W.B. Saunders Company Press, (6th ed.), Philadelphia), pp.493-542.

[5] EVANS, D., (2000) 'Doppler Signal Analaysis', (Ultrasound in Med. & Biol.), pp.13–15,

[6] KEETON P. I. J; SCHLINDWEIN F. S., (1997), 'Application of wavelets in Doppler ultrasound', (Sensor Rev., 17(1)), pp.38–45

[7] SIGEL B., (1998), ‘A brief history of Doppler ultrasound in the diagnosis of peripheral vascular disease', *Ultrasound Med. Biol*, pp.169–176

[8] MILLER A.S; BLOTT B.H.; HAMES T.K., (1992), 'Review of neural network application in medical imaging and signal processing', *Med. Biol. Eng. Comput*, **30**, pp.449-464.

[9] ALLEN J; MURRAY A, (1993), ' Development of a neural network screening aid for diagnosing lower limb peripheral vascular disease from photoelectric plethysmography pulse waveforms’, *Physiol Meas.*, **14**, pp.13-22

[10] UBEYLI E.D.; GULER I., (2003) ‘Neural network analysis of internal carotid arterial Doppler signals: predictions of stenosis and occlusion', *Expert Systems with Applications,* **25**, pp.1-13.

[11] KARA S., (1995), ‘A study of Mitral and Tricuspid valve blood flows by Autoregressive spectral analysis method and Doppler Unit', *Thesis of Doctorate, Institute of Science of Erciyes University Press*,

[12] GÜLER I.; HARDALAÇ F; UBEYLI E.D., (2002), 'Determination of Behcet disease with the application of FFT and AR methods', *Computers in Biology and Medicine*, **32**, pp. 419–434.

[13] GÜLER İ.; KARA S.; GÜLER N.F.; KIYMIK M.K., (1996), ‘Application of autoregressive and fast Fourier transform spectral analysis to tricuspid and mitral valve stenosis', *Comput. Methods Programs Biomed*, Pp.29–36.

[14] SCHLINDWEIN F.S.; EVANS D.H., (1990), 'Selection of the order of autoregressive models for spectral analysis of Doppler ultrasound signals', U*ltrasound Med. Biol.*, pp. 81–91.

[15] SIMPSON P.K., (1989), 'Artificial Neural Systems', *Pergamon Press*.

[16] RUMELHART D.E., HILTON G.E., WILLIAMS R.J, (1986), ‘Learning representations by back-propagating errors', (Nature), **323**, pp.533-536.

[17] BEALE R.; JACKSON T., (1990), 'Neural computing: an introduction', (Bristol, UK: Institute of Physics Publishing).

[18] TÜRKOĞLU I.; ARSLAN A; ILKAY E., (2002), 'An expert system for diagnosis of the heart valve diseases', *Expert Systems with Applications*, **23**, pp. 229–236.

[19] TARASSENKO L.; KHAN Y. U.; HOLT M. R. G., (1998), 'Identification of inter-ictal spikes in the EEG using neural network analysis', *Inst. Elect. Eng. –Proc. Sci. Meas. Technol.*, **145**, pp.270-278.

[20] PANG C. C.; UPTON A. R.; SHINE G.; KAMATH M. V., (2003), 'A comparison of algorithms for deytection of spikes in the Electroencephalogram', *IEEE Trans. Biomed. Eng.*, **50**, pp. 521 – 526.

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