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Neural Network Based Algorithm for Digital Processing of Transcranial Doppler Signal

Key Words: Transcranial Doppler, Ultrasound Doppler, Neural Network, Maximum Frequency Estimation

ABSTRACT

This paper presents a new, neural network based algorithm for estimation of maximum frequency in Transcranial Doppler signal. The comparison of the new algorithm with other, traditional methods has been performed. The presented algorithm features small computational complexity, and good performance even for poor SNR ratio.

1. INTRODUCTION

The estimation of maximum frequency in Transcranial Doppler (TCD) signal is the main tool for noninvasive measurement of blood flow velocity in cerebral vessels. Because of stochastic character of TCD signal, reliable and accurate estimation of its maximum frequency is still an interesting problem for research. New algorithms, based on different methods, are still developed and published. Most of them are based on the analysis of spectral density function [1], however, also completely new ideas are presented [2]. It has been proved [3,4] that spectral density function contains all information necessary to calculate parameters of blood flow profile, however, the exact relationship between estimated power density function and maximum frequency is unknown and difficult to theoretical calculation. Therefore in this work we have tried to apply neural network to calculate maximum frequency from power density function or from the other, easy to calculate parameters of the signal, unambiguously determined by power density function.

2. PROPERTIES OF TCD SIGNAL

Transcranial Doppler Signal results from the scattering of ultrasound wave on moving red blood cells. Frequency of the reflected wave is changed due to Doppler effect. Sidebands of received signal are separated, and after synchronous detection two TCD signals are produced - one associated with blood flow towards the ultrasound transducer, and the other one associ-

ated with blood flow in opposite direction. A more exact description of phenomena associated with backscattering of ultrasound from the blood can be found in [3, 4]. In [3], it has been shown that the normalized power density function of TCD signal is given by equation:

$$p(f)=\begin{cases}\dfrac{2}{kf_{\max}\left(1-\dfrac{f}{f_{\max}}\right)^{1-(2/k)}} & \text{for } f\in[0,f_{\max}]\\ 0 & \text{else}\end{cases} \tag{1}$$

Where f_{max} value is the Doppler shift corresponding to maximum blood flow velocity, and the „k" parameter describes both turbulence in blood flow and aggregation of red blood cells. Its value is equal to 2 for laminar flow without aggregation, and increases for turbulent flow or aggregation. However, because TCD signal can be treated as the superposition of many sinusoids with a random phase, the value of power density function, estimated basing on a short segment of the signal is a random variable, and the above equation describes only the expected value of $p(f)$. It can be shown that the power of signal contained in the narrow frequency bin $[f_0, f_0+\Delta f]$ is a random variable with Rayleigh distribution, and with expected value given by equation (2).

$$E\left(P_{[f_0,f_0+\Delta f]}\right)=\int_{f_0}^{f_0+\Delta f}p(f)\,df \tag{2}$$

2.1 Simulation of TCD signal

To perform training of neural network, and to evaluate different algorithms, we need a TCD signal with known characteristics. The only possibility to obtain such signal is to simulate it using an appropriate model. In this work, the TCD signal has been simulated as the sum of N sinusoids with frequency spaced uniformly from 0 to the Nyquist's frequency. The amplitude of each sinusoid was proportional to the square root of theoretical power density function on its frequency, calculated from equation (1). The phase of each sinusoid was chosen randomly from $[0, 2\pi)$ range. It can be shown that when N is much higher than number of samples of the simulated signal, such superposition of sinusoids has the same stochastic properties as the real TCD signal described above. In our work, we have added 5000 sinusoids, to obtain 128-sample segments of signal. The calculated signal was normalized to obtain unitary power, and then white gaussian noise was added to simulate different signal to noise ratios.

The simulated signal was described by three parameters: the maximum frequency f_{max}, the shape coefficient k (see equation (1)), and the signal to noise ratio SNR.

3. OTHER „REFERENCE" ALGORITHMS OF ANALYSIS OF TCD SIGNAL

Two traditional algorithms have been chosen as the reference for comparison with the new one. To explain these algorithms, we must first define the so called „integrated power spectrum":

$$\Phi(f_x)=\int_0^{f_x}p(f)\,df \tag{3}$$

In the figure 1, explaining both algorithms, f_h is the upper limit of the analyzed frequency band (usually the Nyquist's frequency of sampled TCD signal). The value of integrated power spectrum value on f_h frequency will be denoted as Φ_{max}.

3.1 „Percentile" algorithm

This is the simplest algorithm for calculation of maximum frequency signal. The frequency on which $\Phi(f)$ exceeds the $\alpha \cdot \Phi_{max}$ level is assumed to be the maximum frequency. The α coefficient depends on SNR ratio of TCD signal. Typical values range from 0.8 to 0.9.

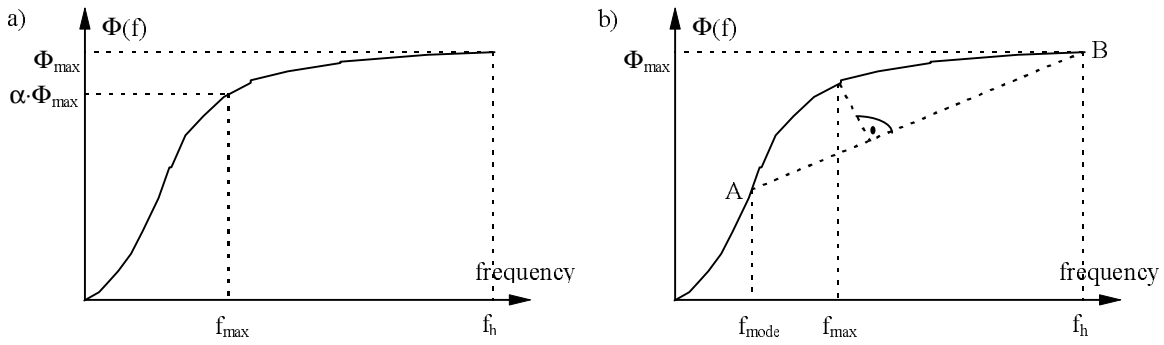

Fig. 1 Illustration of two traditional algorithms of f_{max} estimation: a) "percentile", b) "geometrical" (see explanations in text)

3.2 „Geometrical" algorithm

This algorithm, published in [1], is one of the best algorithms for estimation of f_{max}. The f_{mode} is the frequency of the highest slope of integrated power spectra (frequency of the highest value of power density function). The frequency, on which the distance between integrated power spectrum and AB segment reaches the maximum value, is assumed to be the maximum frequency. A more exact explanation of this algorithm can be found in [1]. The „geometrical" algorithm may be used with various estimators of power density function. In this work, we have used it with FFT, and 6th order AR.

4. NEURAL NETWORK ARCHITECTURE

We have decided to use the „feed forward" network containing units with hyperbolic tangent output function. The estimated f_{max} parameter can take any real value from the range [0,1]. Therefore, we have decided to use a network with single output unit. The value of output function of this unit should correspond to f_{max} . Because we have used units with hyperbolic tangent output function, f_{max} was estimated as the network output value increased by 0.5.

Number of input units depends on signal parameters we use. As it has been stated in section 2, the information about flow velocity distribution is contained in power density function of the signal. Therefore, power density function should be sufficient to calculate maximum blood flow velocity, which is equivalent to determining of f_{max}. However, considering that some (sometimes very simple - e.g. normalization) operations are very difficult to perform in a neural network, we have decided to try also different signal parameters unambiguously determined by power density function:

1) Normalized integrated power spectrum (64 samples)
2) Normalized autocorrelation function (64 samples)
3) Parameters of 10th order AR model (10 parameters)

We started with a simple network, containing only one hidden layer with 64 units, and then we increased number of the hidden layers, until we obtained satisfactory results.

5. TRAINING SET OF SIGNALS

As we mentioned in section 2.1, our simulated signal is described by three parameters: f_{max}, k, and SNR. The training set contained signals generated for all possible combinations of: 100 values of f_{max} from[0.02 f_N, 0.9 f_N] range, 10 values of k from [2,4] range, and 10 values of SNR from [10dB, 3dB] range. The training set contained 10000 of signals and was big enough to assure generalization in the trained network. Two different training sets have been generated - one for training of neural network, and the other for verification of training and for comparison of network's performance with the other TCD signal processing algorithms.

6. RESULTS OF TRAINING

For training of our network, we have used the „Backpropagation with momentum" method, which assured the fastest training. Training of the network with one hidden layer has not given satisfactory results for any signal parameters, used as network's input values. Therefore, we introduced an additional hidden layer containing 10 units. It appeared that the network with two hidden layers, processing normalized autocorrelation function, was able to estimate f_{max} with sufficient accuracy. After the successful training, the network has been pruned. The „Non-contributing Units" method worked the fastest and gave the best results. The pruned network had only 9 input units and used autocorrelation samples from 2nd to 10th. The first hidden layer of the pruned network consisted of 30 units, and the second hidden layer - of 5 units. Total amount of links in the pruned network was equal to 425.

The final structure of our algorithm is shown in the figure 2.

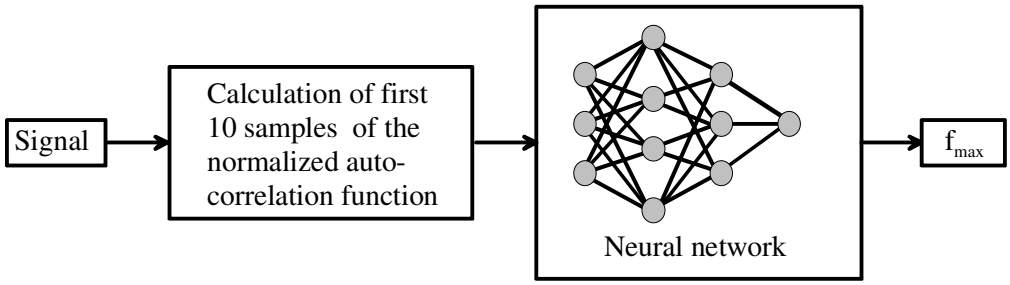

Fig. 2 Block diagram of neural network based algorithm for estimation of f_{max} in TCD signal

7. TESTING OF THE NEW ALGORITHM

To verify the performance of our new neural network based algorithm, we have compared results of f_{max} estimation obtained using our algorithm and two „traditional" algorithms, described in section 3. The testing was performed for both simulated and real TCD signals.

TABLE 1 Comparison of correlation coefficient between real and estimated f_{max} for different algorithms

Algorithm	„Neural"	„Geometrical" with AR	„Geometrical" with FFT	„Percentile" α=0.8	„Percentile" α=0.9
Correlation coefficient	0.997	0.552 0.985*	0.786 0.978*	0.934	0.622

*Calculated after rejection of false, zero results given by „Geometrical" algorithm

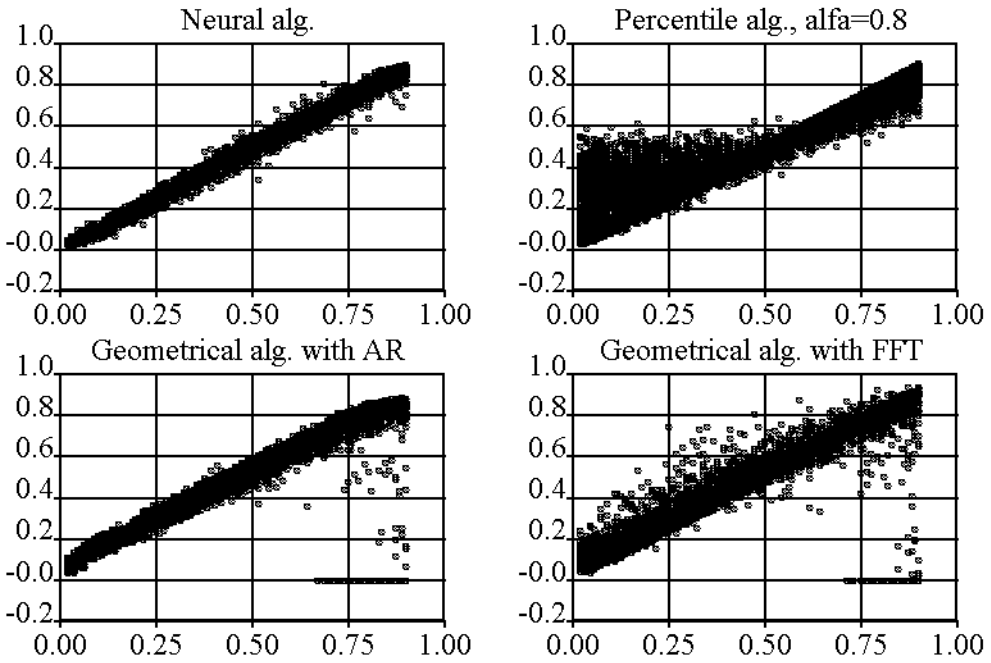

Fig. 3 Scatter plots of estimated f_{max} (Y-axis) versus real f_{max} (X-axis), obtained for different algorithms

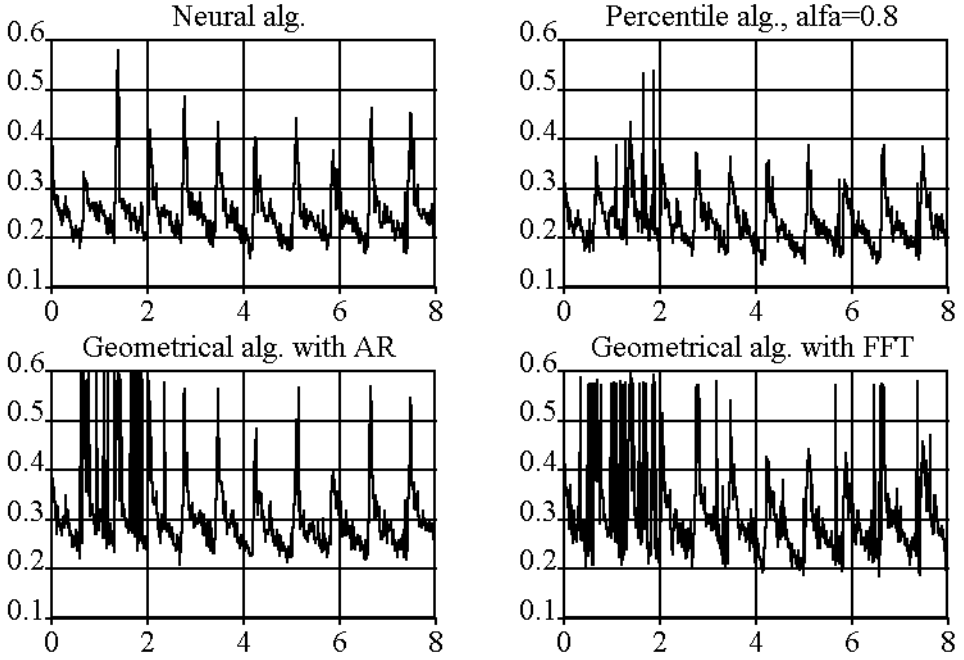

Fig. 4 Results of testing of different algorithms with real signal with disturbances during the first 3 seconds. X-axis: time in seconds, Y-axis: f_{max}/f_N

Results of testing for simulated signals (second training set, not used for training of neural network) are presented in the figure 3.

The correlation coefficients between real and estimated f_{max} have been calculated for each algorithm, and presented in table 1.

The new neural network based algorithm shows the best correlation between real and estimated maximum frequency for simulated signals. The „geometrical" algorithm, reported as the best one, tends to give false zero results for higher f_{max} and worse SNR ratio.

When testing with real signals, we could not compare estimated, and real f_{max}, because the real maximum frequency is unknown. Therefore, we could only evaluate reconstruction of the blood flow pulse wave in the disturbed real signals. Sample results of testing with real signal are presented in the figure 4. Also in analysis of real signal, our new algorithm assures the best elimination of disturbances.

8. CONCLUSIONS

In this work we have proved that neural network may be used for estimating maximum frequency in TCD signal basing on 9 succeeding samples of autocorrelation function (2nd to 10th). The neural network based algorithm has a very small computational complexity - it requires only 425 multiplications and 36 evaluations of hyperbolic tangent (which may by simplified by using look-up tables). The practical implementation of this algorithm in a hardware system, based on DSP56002 processor [6] is about 4 times faster than implementation of FFT-based „geometrical" algorithm, and about 3 times faster than implementation of „percentile" algorithm.

ACKNOWLEDGMENTS

In this work we have used two free software packages: Scilab (http://www-rocq.inria.fr/scilab/) and Stuttgart Neural Network Simulator (SNNS) (http://www.informatik.uni-stuttgart.de/ipvr/bv/projekte/snns/snns.html).

We would like to thank authors of these packages, for making them freely available.

REFERENCES

[1] K. Marasek, A. Nowicki, *„Comparison of the Performance of Three Maximum Doppler Frequency Estimators Coupled with Different Spectral Estimation Methods"*, Ultrasound in Med. & Biol., Vol. 20, No. 7, pp. 629-638, 1994

[2] Y-Y. Wang, W-Q. Wang, *„Fractal Concept and its Analysis Method for Doppler Ultrasound Signals"*, Ultrasound in Med. & Biol., Vol. 19, No. 8, pp. 661-666, 1993

[3] B.A.J. Angelsen *„A Theoretical Study of the Scattering of Ultrasound from Blood"*, IEEE Transactions on Biomedical Engineering, Vol. BME-27, No. 2, Feb 1980

[4] L.Y.L. Mo, R.S.C. Cobbold, *„A Stochastic Model of the Backscattered Doppler Ultrasound from Blood"*, IEEE Transactions on Biomedical Engineering, Vol BME-33, No. 1, Jan 1986, pp. 20-27

[5] Mo, L.C.M. Yun, R.S.C. Cobbold, *„Comparison of Four Digital Maximum Frequency Estimators for Doppler Ultrasound"*, Ultrasound in Med. & Biol., Vol. 14, No. 5, pp. 355-363, 1988

[6] W.M. Zabołotny, W. Zaworski, D. Czarkowski, *„Low Cost PC plug-in Card for Digital Processing of Transcranial Doppler Signal"*, submitted to XX National Conf. on Circuit Theory and Electronic Circuits, Koszalin 1997