The “Context” Algorithms for Estimation of Maximum Frequency in the Nonstationary Transcranial Doppler Signal

Wojciech Zabołotny[+#*], **Przemysław Wołłk-Łaniewski**[%], **Ewa Fersten**[*], **Elżbieta Łuczywek**[*]

[+]Warsaw University of Technology, Institute of Electronic Systems, ul. Nowowiejska 15/19, 00-665 Warsaw, Poland
[#]Tel:(4822) 660 7717, e-mail: wzab@ise.pw.edu.pl
[*]Department of Neurosurgery, Medical Research Center, Polish Academy of Sciences, ul. Pawińskiego 5, 02-106 Warsaw, Poland
[%]Child’s Health Center, Al. Dzieci Polskich 20, 04-736 Warsaw, Poland

ABSTRACT

This paper presents a new concept of algorithms for estimation of maximum frequency (f_{max}) in the nonstationary Transcranial Doppler (TCD) signal. The improvement of estimator’s properties is achieved by exploiting the knowledge about dynamic properties of the blood flow. The raw estimates of f_{max}, calculated with a conventional algorithm for short segments of TCD signal, are smoothed and used as a “hint” for the secondary processing of the signal. This method assures less noisy f_{max} estimates, without the slopes’ flattening, typical for plain linear low-pass filtering of raw estimates.

Keywords: Transcranial Doppler, nonstationary TCD signal, maximum frequency estimation, digital signal processing

1. INTRODUCTION

The Transcranial Doppler (TCD) is an ultrasound device, used for noninvasive measurement of blood flow velocity (BFV) in the cerebral vessels. The pulsed ultrasound signal is emitted as a focused beam and scattered on the flowing blood. The scattered wave, reaching the transducer during a specified time window (depending on the distance between the transducer and the vessel) is subjected to the quadrature detection, giving the in-phase and quadrature components, which are considered the real, and imaginary part of the complex Doppler signal (the TCD signal). If the blood flow velocity (BFV) profile was stationary, the TCD signal would be a wide-sense stationary stochastic process, and it’s power density spectrum (PDS) would

The work reported in this paper was supported by the Grant of Dean of Electronics and Information Technology Faculty of Warsaw University of Technology.

reflect the BFV profile. Particularly the maximum frequency (f_{max}) of the signal should correspond to the maximum blood flow velocity, which is an important parameter in cerebral blood flow (CBF) monitoring.

However, because of the pulsatile blood flow, the TCD signal is nonstationary, and its power density spectrum may be calculated only for short (ca. 10 ms), quasistationary segments. Additionally, the received TCD signal contains also interference, which is usually considered to be the additive white noise. The SNR ratio may be as low as 0 dB, while values of 10 dB are considered as good. The necessity of PSD calculation from short segment of single realization of the stochastic TCD signal, results in noisy estimates of f_{max}. If we increase the length of such a segment, the variance of both: PSD estimate, and f_{max} estimate will decrease, but the bias caused by signal's nonstationarity will increase.

In our previous work [1], we have proposed a method using the neural network to extract less noisy f_{max} estimates from parameters of a few consecutive signal's segments. This method may be called a "context" neural method.

In this paper we show, that similar approach - combining of information contained in a few consecutive short signal segments - may be used to improve the "classical" (ie. nonneural) f_{max} estimators.

2. CONCEPT OF THE "CONTEXT" ALGORITHM OF f_{max} ESTIMATION

In this method we imitate the analysis of TCD signal's spectrogram, performed by a human. When looking for a maximum frequency in the particular segment of the signal, the human considers its context - the spectrum of the signal in the adjacent blocks. If there are few possible values of f_{max}, he will prefer this one, which best fits the f_{max} trend deduced from this one and adjacent signal's segments. Certainly this process involves an *a priori* knowledge about the properties of the trend of maximum frequency.

To reproduce this process in an algorithm, we have proposed the structure shown in the Fig.1.

The TCD signal is divided into segments, and for each segment the f_{max} is calculated with any known algorithm (further referred to as "plain algorithm"). The obtained m "raw" f_{max} estimates are then smoothed, to calculate the "suggested" f_{max} value for the central (nth) segment. This value is then used as a hint for a secondary processing of this segment, with an algorithm (further referred to as "hinted algorithm") modified to prefer the f_{max} values near to the "suggested" value.

Comparing to the traditional methods of f_{max} estimation, our context method uses two new components: the smoothing algorithm, and the "hinted" algorithm of f_{max} estimation. We will describe them more thoroughly in the next sections.

3. SMOOTHING OF THE RAW f_{max} ESTIMATES

Because of dynamic properties of the blood flow, we may assume, that the maximum frequency of the TCD signal is a continuous function of the time with existing second derivative.

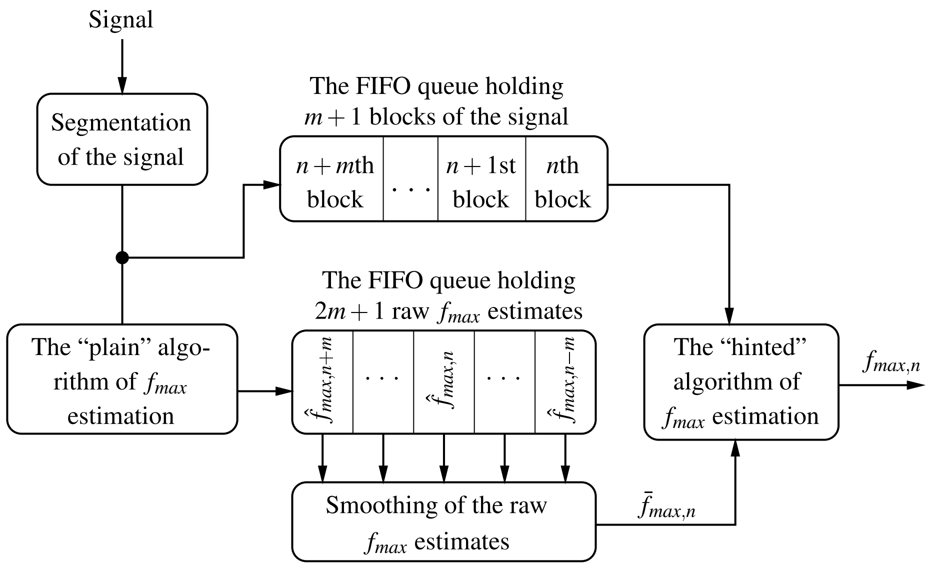

Fig. 1. The general structure of the m-th order "context" algorithm of f_{max} estimation.

Basing on this assumption we have proposed two methods of smoothing. The first uses the polynomial approximation of the f_{max} trend, and the second one - the Kalman filter.

3.1. Smoothing of f_{max} estimates with the polynomial approximation

In this method we have assumed that due to the mentioned above properties of the $f_{max}(t)$ trend, its short part may be approximated with the parabola's segment. The smoothing of $2m+1$ raw estimates $(f_{max}(t_{n-m}),\ldots,f_{max}(t_{n+m}))$ is performed by finding the best fitted (in least squares sense) 2nd order polynomial, and then taking its value for t_n. This algorithm seems to require complex calculations (eg. polynomial fitting), but in fact, for fixed m, it is equivalent to linear filtering of raw estimates through the FIR filter with coefficients given by the first row of matrix **B**:

$$\mathbf{B} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T \tag{1}$$

where matrix **X** is defined as follows:

$$\mathbf{X} = \begin{bmatrix} 1 & -m & (-m)^2 \\ \vdots & \vdots & \vdots \\ 1 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 1 & m & m^2 \end{bmatrix} \tag{2}$$

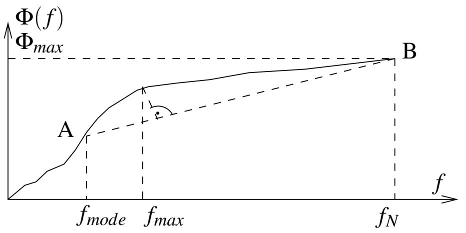

Fig. 2. The geometrical method of f_{max} estimation.

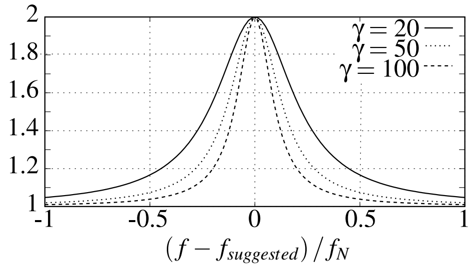

Fig. 3. Plot of the correction function for sample values of γ coefficient.

3.2. Smoothing of f_{max} estimates with the Kalman filter

In this method we have investigated a very simple signal model with state vector consisting of three values of f_{max} for consecutive signal's segments. The state equation, based on the similar assumptions as in the previous method was:

$$f_{max,n+1} = 3f_{max,n} - 3f_{max,n-1} + f_{max,n-2} + w_n \tag{3}$$

where scalar w_n is the input noise. Because of unknown variances of both input and output noises the problem requires an adaptive Kalman filter. However this would unacceptably increase the computational complexity of the algorithm. To avoid it, we assumed the equal variances of both noises and used a steady state approximation. The resulting Kalman filter was a 3-rd order IIR filter, with $H(z)$ given by the equation:

$$H(z) = \frac{-0.0327840 + 0.1519070z + 0.2397643z^2}{-0.1288001 + 0.6261646z - 1.1384772z^2 + z^3} \tag{4}$$

4. THE "HINTED" ALGORITHM FOR f_{max} ESTIMATION

The second new component of the context method is the "hinted" algorithm of f_{max} estimation. It should be the same algorithm as used to obtain the raw estimates, but modified to prefer the values near to the "suggested" value of maximum frequency.

In our work we have used the geometrical algorithm coupled with the AR-based PSD estimator, described by Marasek and Nowicki in [3], which provides the best f_{max} estimates among different nonneural algorithms of f_{max} estimation. The geometrical algorithm (see Fig.2.) uses the integrated power spectrum, defined by the formula:

$$\Phi(f_x) = \int_0^{f_x} G(f)df \tag{5}$$

First we find the frequency f_{mode}, where the power density spectrum reaches its maximum. Then we connect two points in the plot of integrated power spectrum: A - corresponding to the f_{mode} and B - corresponding to the Nyquist's frequency f_N. The maximum frequency corresponds to the point of the plot, which is most distant from the AB line. In the modified

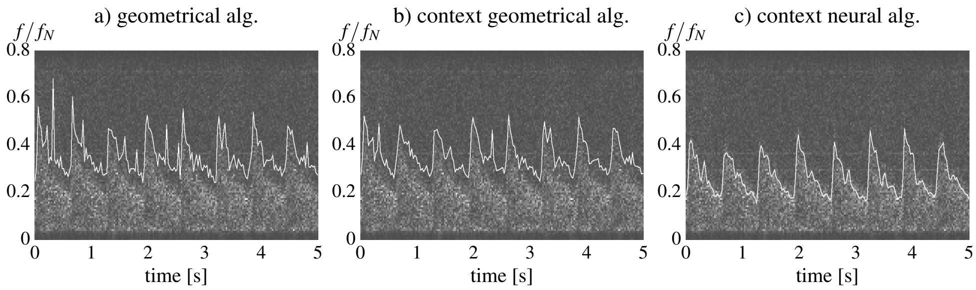

Fig. 4. Results of testing of different algorithms with the real signal.

version of the geometrical algorithm we are looking for the maximum of the above distance, multiplied by the so called "correction function". The correction function takes the maximum value for the "suggested" frequency, and decreases smoothly with the increase of distance from the suggested frequency. In our work we have used the function defined by the following formula:

$$f_{cor}(f) = 1 + \frac{f_N^2}{f_N^2 + \gamma\left(f - f_{suggested}\right)^2} \tag{6}$$

The plots of this function for different values of γ parameter are shown in the Fig.3.. The best results were obtained for $\gamma = 20$.

5. TESTING AND RESULTS

To evaluate our new, context approach to the f_{max} estimation, we have compared results obtained with four algorithms: the plain geometrical method [3], the new context geometrical method, the plain neural method [2], and the context neural method [1]. The algorithms were tested with both real and simulated signals. The simulated signals with known parameters were generated with the model of nonstationary TCD signal presented in [1]. The values of the "flatness" coefficient k and of the SNR in simulated signals are shown in the Table 1. The f_{max} trend for simulated signals was extracted from sample clinically recorded signals.

To compare the different algorithms, we calculated the RMS error of estimation. The obtained results are shown in the Table 1. The context version of geometrical algorithm gave less RMS error then the plain version. However the obtained results were generally worse, then those given by neural algorithms, both: plain and context.

The real test signals were recorded clinically. We didn't know the exact $f_{max}(t)$ values for this signals, so the comparison of algorithms was only subjective. We evaluated the smoothness of the obtained f_{max} trend and its relationship to the signal's spectrogram. The sample results for three algorithms are shown in the Fig. 4. We can see, that context method eliminates the especially annoying "spikes" in the estimated f_{max} trend, without the flattening of the rising slope of this signal.

Table 1. Results of testing of different algorithms with the simulated signals.

Signal parameters		**The RMS error for different methods**			
		geom. + AR		**neural**	
SNR	k	plain	context	plain	context
0	2	0.0577	0.0450	0.0688	0.0471
0	4	0.0736	0.0719	0.0447	0.0263
0	10	0.1311	0.1105	0.0558	0.0201
3	2	0.0420	0.0389	0.0442	0.0401
3	4	0.0647	0.0639	0.0252	0.0164
3	10	0.0764	0.0758	0.0210	0.0148
10	2	0.0297	0.0271	0.0263	0.0275
10	4	0.0614	0.0611	0.0226	0.0148
10	10	0.0729	0.0726	0.0172	0.0151

6. CONCLUSIONS

The new "context" approach for estimation of maximum frequency in the nonstationary TCD signal, presented in this work, allows to decrease the f_{max} estimator's variance. It is especially efficient in eliminating the annoying "spikes" in estimated f_{max} trend, occurring particularly in low SNR conditions.

The computational complexity of the context algorithm is approximately two times higher then complexity of analogous plain algorithm.

The comparison of the new context method and neural methods suggests that further research is still required. The use of nonlinear smoothing algorithms should probably assure further improvement of the estimator's properties.

REFERENCES

[3] K. Marasek and 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, July 1994, pp. 629–638.

[2] W. M. Zabołotny, P. Wołłk-Łaniewski, E. Łuczywek, E. Fersten, Application of Neural Networks in Estimation of Maximum Frequency in Transcranial Doppler Signal, *Proc. of the 8-th International IMEKO Conference on Measurement in Clinical Medicine*, Dubrownik, 1998, pp. 3-67 – 3-70.

[1] W. M. Zabołotny, P. Wołłk-Łaniewski, E. Fersten, E. Łuczywek, Estimation of Maximum Frequency in the Nonstationary Transcranial Doppler Signal - Neural Network Based Approach, *Proc. of the XXI-st National Conference Circuit Theory and Electronic Networks*, Poznań-Kiekrz, 1998, pp. 529–534.