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# Estimation of Maximum Frequency in the Nonstationary Transcranial Doppler Signal - Neural Network Based Approach

**Keywords:** Transcranial Doppler, modelling of nonstationary TCD signal, maximum frequency estimation, neural networks, digital signal processing

## ABSTRACT

This paper presents a new, neural network based method for estimation of maximum frequency ($f_{max}$) in the nonstationary Transcranial Doppler (TCD) signal. In this new approach the signal is divided into short segments to decrease error associated with a change of $f_{max}$ in the single segment, and then information extracted from a few subsequent segments is combined to decrease the variance of the maximum frequency estimator. Additionally a model for simulation of nonstationary TCD signal is presented.

## 1. INTRODUCTION

The Transcranial Doppler (TCD) is the ultrasound device allowing the non-invasive measurement of blood flow velocity (BFV) in the cerebral vessels. The ultrasound beam is scattered on the flowing blood and its frequency is shifted due to the Doppler effect. The BFV profile is mapped into the power density spectrum of TCD signal. In the long term monitoring of cerebral blood flow the parameter of high importance is

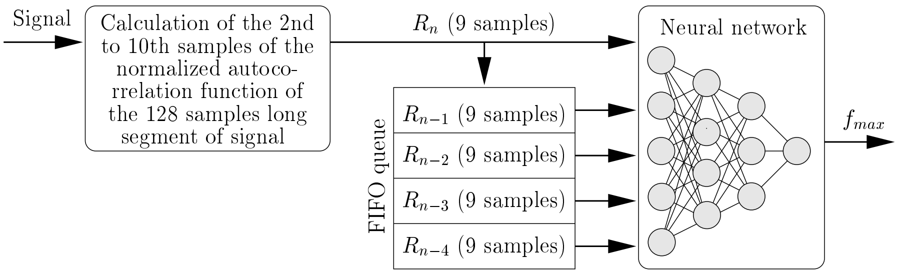



Fig. 1. Structure of the proposed algorithm

the maximum frequency ($f_{max}$) of this signal. The $f_{max}$ is the frequency corresponding to the blood flow velocity in the centre of the vessel (the maximum instantaneous blood flow velocity in the vessel).

In formerly presented algorithms of $f_{max}$ estimation, the signal was divided into segments short enough ($\approx$ 10 ms) to allow assumption that in the whole segment blood flow velocity remains practically constant. Because of the stochastic nature of the TCD signal [1, 3], the variance of the estimated $f_{max}$ is the higher, the shorter the segments are. However increasing of segments' length increases the error caused by non-constant BFV in the segment.

In this work we have proposed a method which uses short signal segments, but combines information contained in a few subsequent segments to obtain less noisy $f_{max}$ estimator. We utilize the fact that both: maximum blood flow velocity and $f_{max}$ are continuous functions of time. Therefore the parameters of signal in preceding and following segments contain an additional information useful for estimation of $f_{max}$ in the particular segment.

The relationship between $f_{max}$ in a single segment and signal parameters in this one and adjoining segments is very difficult for theoretical derivation. Therefore we have decided to use a neural network for approximation of this unknown relationship.

## 2. STRUCTURE OF THE ALGORITHM

The structure of the proposed algorithm is shown in the Fig. 1. The sampled TCD signal is divided into segments with length of 128 samples (12.8 ms at sampling frequency 10 kHz). Each segment is then subjected to the preprocessing, to filter out all signal features not necessary for estimation of maximum frequency. Basing on the results presented in [5] we have decided to calculate the 9 samples (from 2nd to 10th) of the normalized autocorrelation function. The signal parameters obtained in the preprocessing are then stored in the FIFO queue, holding the 4 previously calculated parameters sets. The autocorrelation samples calculated for 5 subsequent segments are then used as input values for the neural network, trained to estimate the maximum frequency of the signal contained in the 3rd (middle) segment.

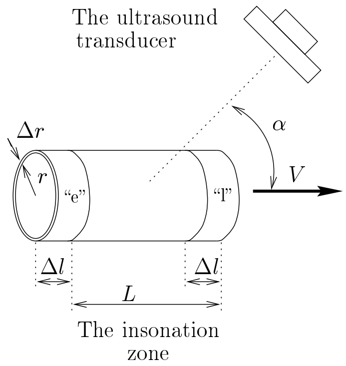



Fig. 2. Single layer of blood stream in the insonated part of the vessel

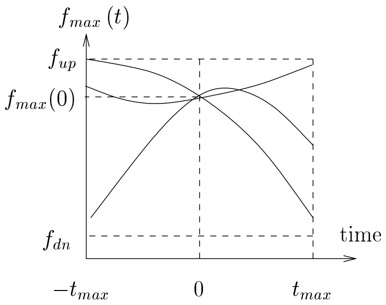



Fig. 3. Time plots of $f_{max}$ in the simulated signals

## 3. GENERATION OF SIMULATED SIGNALS

To perform training and testing of the neural network it was necessary to have set of TCD signals with well known parameters and with varying in time maximum frequency. The only possibility to obtain such a signal is to simulate it with the appropriate model.

### 3.1. Model of the nonstationary TCD signal

Our model simulates the process of TCD signal formation. We assume, that the blood flows in a cylindric vessel with radius $R$, and its flow velocity depends only on the distance from the vessel's centre $r$. The following relationship between layer's radius and BFV was assumed [1, 4]:

$$V(r) = V_{max}\left(1 - \left(\frac{r}{R}\right)^k\right) \text{ for } 0 < r < R \text{ and } 2 \leq k < \infty \tag{1}$$

Where $R$ is the vessel's radius and $k$ is the coefficient describing the "flatness" of the BFV profile. The $f_{max}$ is determined by the formula:

$$f_{max} = 4\pi\omega\frac{V_{max}}{c}\cos\alpha \tag{2}$$

where $c$ is the ultrasound velocity in blood, $\alpha$ is the angle between the BFV vector and ultrasound beam, and $\omega$ is the pulsation of ultrasound wave.

We consider a thin single layer with radius $r$ and thickness $\Delta r$ (see Fig. 2.). Length of the insonated part of vessel is $L$. The in-phase and quadrature signals obtained after the synchronous detection are respectively $I(t)$ and $Q(t)$. The algorithm for calculation of subsequent samples of this signals is presented in the Fig. 4., however because of the lack of space its derivation is not presented. The additional symbols introduced in this algorithm are: $\beta$ - the constant describing the intensity of

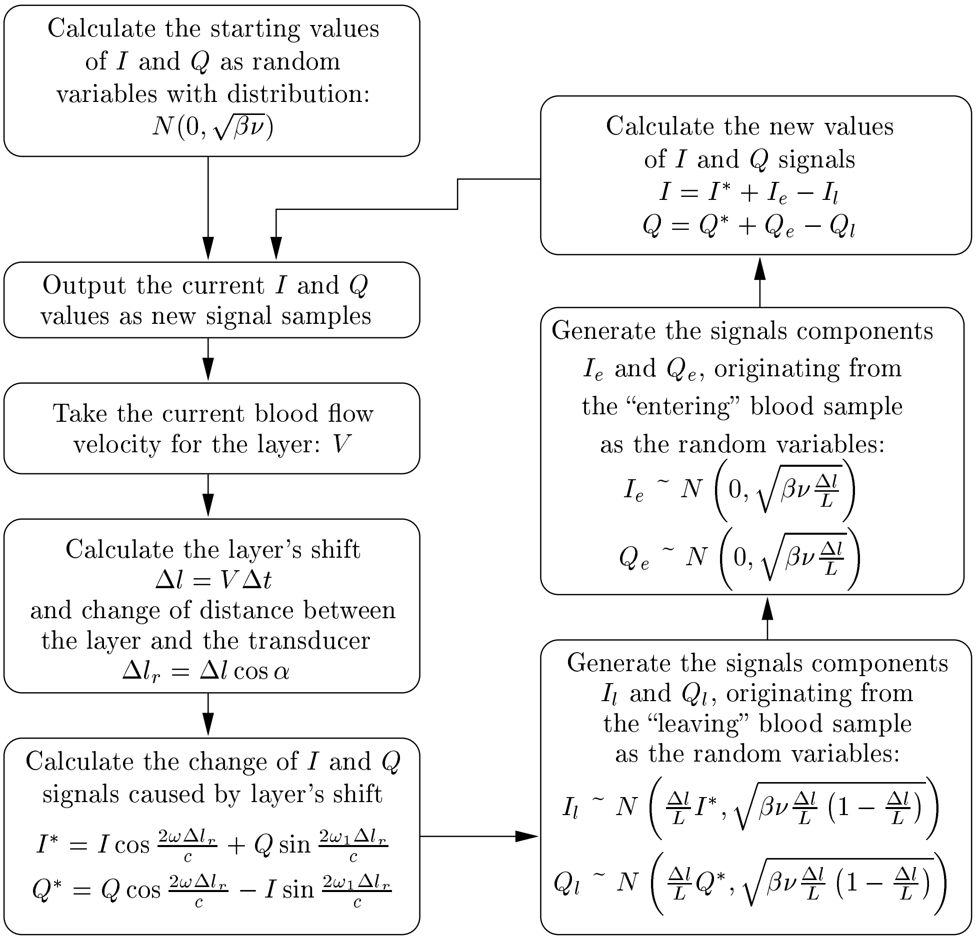



Fig. 4. Algorithm for generation of subsequent samples of nonstationary TCD signal

ultrasound scattering and $\nu$ - the layer's volume. To get the $Q$ and $I$ signals from the whole insonated vessel we have to sum contributions from all the layers. In our work we divided the blood's stream into 1000 layers. Because we wanted to simulate only the unidirectional flow, only the $I$ signal was used as a simulated TCD signal. Finally the white noise is added to obtain the desired SNR level. The signals generated with this model were very similar to the real TCD signals recorded in the patients. The formulated algorithm of generation of nonstationary TCD signal is very versatile. It may be used for different relationships between the layer's radius and flow velocity.

### 3.2. Generation of the training and testing patterns

To train our network we needed the representative set of signals. We have generated set containing 10000 signals with 10 different SNR levels from range [10 dB, 0 dB], 10 different values of "flatness" coefficient $k$ from range [2,10] and 100 different $f_{max}(0)$ (maximum frequency in the middle of the signal - the value which the neural network is trained to estimate) values from range $[0.03\ f_N,\ 0.9\ f_N]$. Additionally, for each signal the $f_{max}(t)$ curve was randomly generated, to obtain the maximally representative class of training patterns. We made an assumption that during the short time the $f_{max}(t)$ curve may be approximated with the segment of parabola (see Fig. 3.). The parabola's coefficients were selected randomly, and special algorithm has been developed to generate only parabolas meeting the below limitations for each $t \in [-t_{max}, t_{max}]$:

$$f_{dn} < f_{max} < f_{up} \tag{3}$$

$$\left|\frac{df_{max}}{dt}\right| < \gamma_1 \tag{4}$$

$$\left|\frac{d^2 f_{max}}{dt^2}\right| < \gamma_2 \tag{5}$$

The $f_{dn}$ parameter was set to $0.03 f_N$, and $f_{up}$ to $0.91 f_N$. The $\gamma_1$ and $\gamma_2$ were selected basing on properties of blood flow velocity waveforms.

## 4. NEURAL NETWORK'S STRUCTURE AND TRAINING

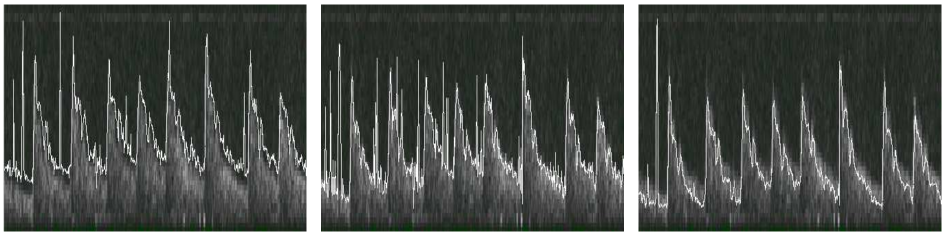
The fully connected feed forward network with two hidden layers (45 inputs, 40 units in the first hidden layer, 16 units in the second hidden layer and 1 output unit) has been used. Because we have used units with the hyperbolic tangent output function, the output value of the network was equal to $f_{max} - 0.5$. The network was trained with the "Backpropagation with momentum" method, which assured the fastest training. The trained network was pruned with the "Non-contributing Units" method. The final, trained and pruned, network had 27 inputs, 1093 links, 34 units in the 1st hidden layer, 5 units in the 2nd hidden layer and one output unit.

## 5. RESULTS

The whole algorithm was tested with simulated and real signals, and compared with other algorithms - the "geometrical" described in [2] and "simple neural" described in [5]. The new algorithm gave less biased and less noisy estimate of $f_{max}$ than the others. The sample results of testing with the real signal are presented in the Fig. 5.

## 6. CONCLUSIONS

The model of nonstationary TCD signal presented in this work appeared to be an useful tool for generation of artificial TCD signals with well known, changing with time parameters. The proposed method for estimation of maximum frequency performs better than others, formerly published methods [2,5], assuring less variance of maximum frequency estimator. Because of relatively small computational complexity



a) geometrical alg. b) simple neural alg. c) new neural alg.

Fig. 5. Result of processing the real signal with different algorithms (Y-axis: frequency 0 to $0.8 f_N$, X-axis: time 0 to 6.4 s, background - the power density spectrum, white line - the estimated $f_{max}$)

and small amount of divisions, the new method is well suited to implementation in a DSP software.

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