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Adaptive Wavelet Analysis of Optical Coherent Tomography Data: Application in Problems of Diagnostics

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Abstract—A method of adaptive wavelet analysis permitting one to set parameters of the wavelet transform based on principles of the optimization theory is proposed. Applying the method to optical coherent tomography data processing is considered. The efficiency of the proposed method for diagnosing functional disorders in the dynamics of cerebral vessels is illustrated.

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The problem of extracting information on the dynamics of a studied system from the analysis of optical coherent tomography (OCT) data [1, 2] is an urgent problem important for the development of technical possibilities of monitoring the current state of the system. In particular, solving this problem favors improving the technical basis for designing medical diagnostic complexes intended for early detection of functional disorders in the dynamics of cerebral blood vessels. One way to solve this is to perform time-and-frequency analysis of the blood flow with use of wavelet-analysis methods ensuring the possibility to obtain estimates of local spectral characteristics by short-time signals and nonstationary data [3–6]. However, the efficiency of these methods depends on an appropriate setting of wavelet transform parameters, the unsuccessful choice of which reduces the reliability of the revelation of changes in the structure of signals with a change in the state of the system. To eliminate this disadvantage, this work proposes an adaptive approach based on the optimization theory.

Let us consider an example of a Doppler OCT image of a blood vessel (Fig. 1) where the color gradation is connected with the velocity and direction of scattering particles, i.e., with the blood flow rate. Selecting a point positioned inside the vessel (within the A contour) and tracing the variation of the color gradation in time for the sequence of B_0 images (OCT scans) make it possible to pass on to studying the temporal dynamics $s(t)$, $t = i\Delta\tau$, $i = 1, \ldots, N_0$, $N_0\Delta\tau = T$, where $\Delta\tau$ is the time interval between two scans and T is the duration of signal $s(t)$. Reaction to an external action is an important index of vessel functioning; for this reason, the proposed method is based on comparing the characteristics of two functioning modes—before and after the action ($s_0(t)$ and $s_1(t)$, respectively).

When analyzing a relatively short sequence of OCT scans, it seems suitable to perform preliminary experimental data processing that includes interpolation of signals $s_0(t)$ and $s_1(t)$ with step Δt, e.g., by cubic splines $S_0(t)$ and $S_1(t)$ and digital filtration using a low-frequency filter to eliminate high-frequency variations and artifacts. One simple version of the filtration is the moving average method, the use of which results in passage to processes $F_0(t)$ and $F_1(t)$. An example of preliminary processing of the experimental OCT data is presented in Fig. 2. Below, analysis of signals $F_0(t)$

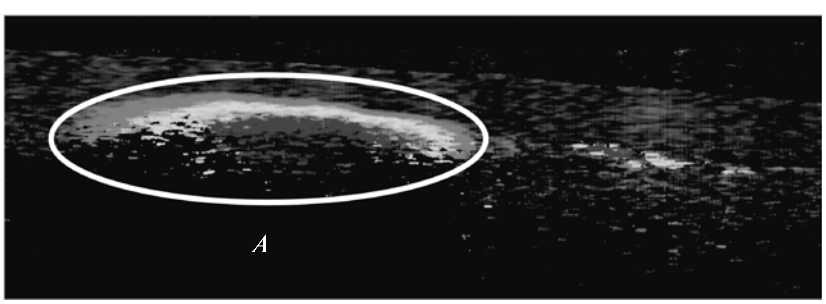

Fig. 1. Example of an image obtained by OCT of a cerebral vessel of a rat.

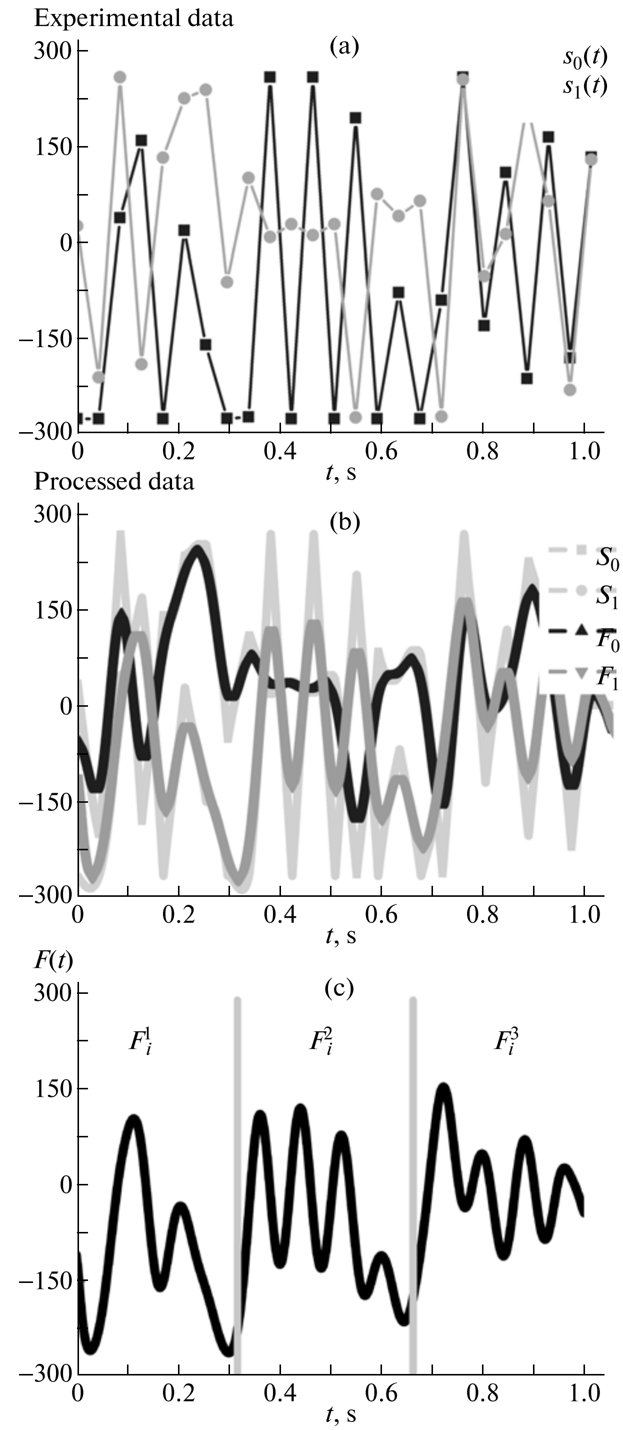

Fig. 2. Analyzed processes: (a) initial experimental data in the form of signals $s_0(t)$ and $s_1(t)$, (b) processed data after the interpolation $S_0(t)$ and $S_1(t)$, and the interpolation and filtration of $F_0(t)$, $F_1(t)$, and (c) partition of process $F(t)$.

and $F_1(t)$ after they pass the procedure of preliminary processing is performed based on wavelet analysis, which is one of most efficient tools for studying the time-and-frequency composition of experimental data.

The continuous wavelet transform of signal $F(t)$ can be written in the following form:

$$W(\nu; t) = \sqrt{\nu}\int_0^T F(t')\varphi^*(\nu(t'-t))dt', \tag{1}$$

$$t' = k\Delta t, \quad t = j\Delta t,$$

where $W(\nu; t)$ are wavelet coefficients, φ is the basis function, parameters t and ν characterize the wavelet shift along the time axis and scale variations of the basis function, Δt is the discretization interval after interpolation by the splines ($\Delta t < \Delta\tau$), and the asterisk denotes complex conjugation. In this work, the Morlet wavelet

$$\varphi(x) = \pi^{-1/4}\exp(i\omega_0 x)\exp(-x^2/2) \tag{2}$$

is used as a basis function. It is well localized both in the temporal and spectral regions. The time-and-frequency resolution is corrected by specifying the parameter ω_0, the central frequency of the wavelet. To reveal the most significant particularities in the dynamics in two operation modes, i.e., to find maximal differences between processes $F_0(t)$ and $F_1(t)$, it is necessary to select the optimum set of the parameters ν and ω_0. For this purpose, each of the processes is partitioned into P_F segments with duration M_F each ($N_F = P_F M_F$, $N_F\Delta t = T$), which makes it possible to bring into consideration the fragments $F_i^j = F(i\Delta t)$, $i \in [jM_F; (j+1)M_F)$, $j = 0, 1, \ldots, P_F$, and the corresponding wavelet coefficients $W_j(\nu, \omega_0, t)$. Note that, in contrast to formula (1), these coefficients depend on three parameters, with allowance for the additional parameter ω_0 of wavelet function (2). Using the obtained coefficients, we calculate the mean amplitude A for each fragment of the analyzed process:

$$A_j(\nu, \omega_0) = \frac{1}{M_F}\sum_{k=1}^{M_F}\left|W_j(\nu, \omega_0, t)\right|. \tag{3}$$

Thus, two sets of local mean amplitudes $A_j^0(\nu, \omega_0)$ and $A_j^1(\nu, \omega_0)$ are calculated for processes $F_0(t)$ and $F_1(t)$. Based on them, it is proposed to construct an objective function of the local mean maximum $R_d(\nu, \omega_0)$:

$$R_d(\nu, \omega_0) = \frac{\langle A_j^1(\nu, \omega_0)\rangle - \langle A_j^0(\nu, \omega_0)\rangle}{\sigma(A_j^0(\nu, \omega_0)) + \sigma(A_j^1(\nu, \omega_0))}, \tag{4}$$

where the angular brackets denote averaging over the ensemble of the quantities $A_j^0(\nu, \omega_0)$ and $A_j^1(\nu, \omega_0)$, i.e., over the index $j = 0, 1, \ldots, R_F$, and σ is the root-mean-square deviation of the quantities $A_j^0(\nu, \omega_0)$ and $A_j^1(\nu, \omega_0)$ from values averaged over index j. The choice of function (4) is caused by the necessity to find parameters that maximize differences between mean values of amplitudes with respect to variations of these values for different parts of signals. Using objective function (4), one can determine optimum values of parameters ν and ω_0 at which maximal differences in analyzed processes $F_0(t)$ and $F_1(t)$ are revealed in the frequency range. If the parameters are chosen optimally or closely to the optimum level, function (4) takes values lying in the range $(-\infty; -1] \cup [1; +\infty)$. For all other values of objective function (4), differences between the analyzed processes are small.

Thus, the proposed algorithm is adaptive by virtue of the fact that parameters ν and ω_0 are chosen using the introduced objective function (4). It is proposed to carry out the process of searching for the parameters based on the stochastic optimization method (algorithm of Monte Carlo statistical trials [7, 8]), which can be written in the form of the following algorithm.

(1) Generation of random values of parameters ν and ω_0 of the Morlet function within the given frequency range.

(2) Calculation of values of the objective function $R_d(\nu, \omega_0)$.

(3) Sorting the sequence of values of the objective function [9] and obtaining a static series the extreme values of which point to the optimum values of the parameters ν and ω_0, choosing the first or the last value of the static series depending on which of them is larger in the absolute value.

In this work, the proposed adaptive method was applied for quantitative description of changes in the dynamics of cerebral blood vessels of rats administered with adrenaline; $s_0(t)$ and $s_1(t)$ characterize the blood velocity before and after the change in the adrenaline level in blood, respectively. Under pathological conditions (vessel-functioning disorders resulting in cerebral bleeding), the reaction to adrenaline is weaker as compared to the norm; this corresponds to relatively small values of the objective function $R_d(\nu, \omega_0)$. This makes it possible to introduce the following quantitative criteria:

$$\theta = \frac{1}{2}(\langle|R_d|\rangle^n + \langle|R_d|\rangle^p), \quad \alpha = \frac{\langle|R_d|\rangle^n}{\langle|R_d|\rangle^p}, \tag{5}$$

where n and p correspond to values of the objective function for normal and pathological cases and the angular brackets denote averaging.

The proposed method was tested on experimental records of OCT signals of five rats ($\Delta\tau = 0.14$ s and $N_0 = 50$ for each state). After interpolation and filtration ($N_F = 15\,000$ and $\Delta t = 0.00047$ s), the signals were divided into $P_F = 3$ segments with duration $M_F = 5000$, which was followed by stochastic optimization of the objective function for all experiments. The optimization was performed separately in ranges reflecting the influence of different regulation mechanisms: 0.25–0.75 (the LF range), 0.75–3.0 (the HF range), and 5.0–10.0 Hz (the range of the heartbeat frequency). The optimization results for $R_d(\nu, \omega_0)$ and values of oscillation frequency f corresponding to optimum val-

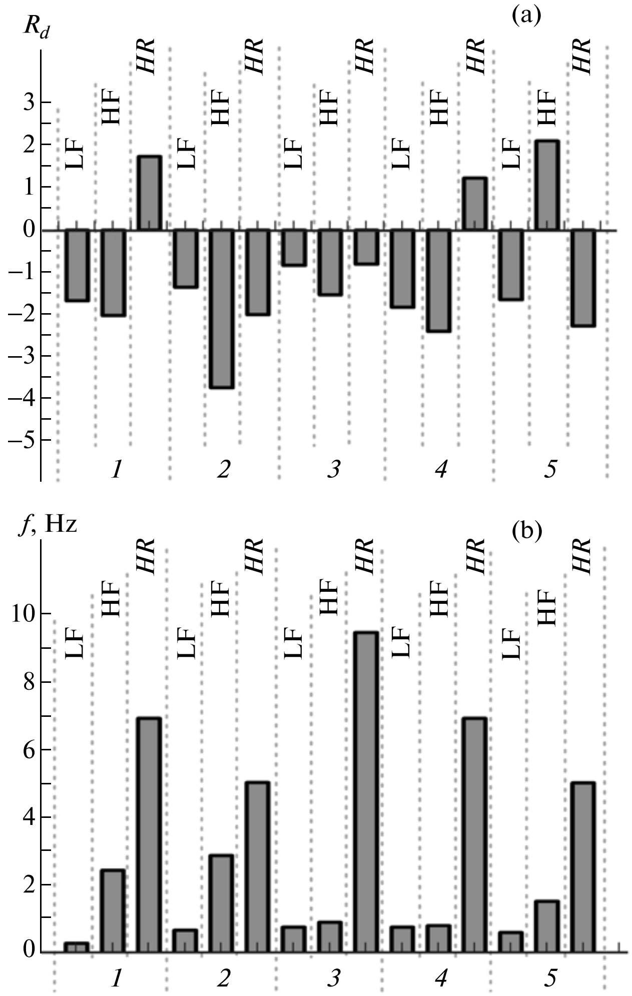

Fig. 3. Results of stochastic optimization: (a) values of the objective function R_d and (b) frequency corresponding to optimum values of parameters of the Morlet function.

ues of parameters ν and ω_0 are presented in Fig. 3. The oscillation frequency was calculated by the formula

$$f = \nu\frac{\omega_0 + \sqrt{\omega_0^2 + 2}}{4\pi}, \tag{6}$$

which characterizes the relationship between parameters of the wavelet function and frequency of the Fourier spectrum. The clearest distinctions between normal and pathological cases were revealed in the LF range and correspond to values $\theta = 1.23$ and $\alpha = 1.9$. Criteria (5) exceeding these values correspond to the normal dynamics. Note that applying classical spectral analysis did not make it possible to reliably distinguish between normal and pathological dynamics, which indicates a higher potential of wavelet-analysis methods in processing short-time signals. The proposed method of adaptive analysis ensures the possibility of automatic revelation of the most significant distinctions of the dynamics in different states and is implemented in the form of an algorithm that does not require direct participation of the investigator in parameter setting. Thus, the influence of human factors (such as the investigator's experience) is eliminated, and this circumstance opens wide prospects for applying this approach in designing automated diagnostic complexes for early detection of functional disorders in vessel dynamics.

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REFERENCES

1. J. G. Fujimoto, in *Encyclopedia of Optical Engineering*, Ed. by R. Driggers (Marcel Dekker, New York, 2003), p. 1594.
2. *Optical Coherence Tomography: Technology and Applications*, Ed. by W. Drexler and J. G. Fujimoto (Springer, Berlin, 2008).
3. S. G. Mallat, *A Wavelet Tour of Signal Processing* (Academic Press, New York, 1998).
4. P. S. Addison, *The Illustrated Wavelet Transform Handbook: Introductory Theory and Applications in Science, Engineering, Medicine and Finance* (IOP Publishing, Bristol, 2002).
5. A. N. Pavlov, V. A. Makarov, E. Mosekilde, et al., Brief. Bioinform. **7**, 375 (2006).
6. A. N. Pavlov, A. E. Hramov, A. A. Koronovskii, et al., Phys. Usp. **55**, 845 (2012).
7. R. Yuan, D. Yu, and L. Faming, Stat. Comput. **18**, 375 (2008).
8. M. Papadrakakis and N. D. Lagaros, Comput. Meth. Appl. Mech. Eng. **191**, 3491 (2002).
9. T. H. Cormen, C. E. Leiserson, R. L. Rivest, and C. Stein, *Introduction to Algorithms*, 3rd ed. (MIT Press, Cambridge, 2009).

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