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Use of Wavelets for Recognizing Types of Motion by Means of Data on the Electrical Activity of the Brain

D. S. Grishina[a], A. N. Pavlov[a,b]*, O. N. Pavlova[b], and A. E. Runnova[c]

[a] *Yuri Gagarin State Technical University of Saratov, Saratov, 410054 Russia*
[b] *Saratov State University, Saratov, 410012 Russia*
[c] *Innopolis University, Innopolis, Tatarstan, 420500 Russia*
**e-mail: pavlov.alexeyn@gmail.com*

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Abstract—We consider the task of oscillatory pattern recognition on the fragments of electroencephalogram records obtained during motion and their mental representation for the development of a neurointerface software. Using a multiscale analysis, the number of channels is estimated that will provide reliable separation of motions of various types from background activity.

Keywords: signal, pattern recognition, wavelet analysis, filtration.

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Achievements in the creation of brain–computer interfaces (BCIs or neurointerfaces) [1–5] led to the formation of a new field of interdisciplinary research where a number of original R&D projects have been proposed in recent years. BCIs provide recognition of the characteristic features of detected signals—e.g., records of the electrical activity of the brain in the form of electroencephalograms (EEGs)—and the subsequent formation of commands controlling hardware. These interfaces allow various actions in the environment to be accomplished based on mental intentions without using muscles [6–10], which is especially important for people with serious motor disabilities. Existing BCIs already allow paralyzed people to drive cursor movements on a display screen, synthesize voice communications, control motions, etc.

A key role in the creation of BCIs belongs to the software intended to detect and recognize signal patterns corresponding to various mental intentions. These programs must rapidly reveal characteristic signs of patterns from short signal fragments with allowance for their variability, which is a complicated task that requires using special methods [10—15]. In particular, it is possible to apply, e.g., approaches based on wavelet analysis [16, 17] or fluctuation analysis [18, 19]. These tools are capable of solving the tasks of recognizing motions, but existing methods [17] do not ensure sufficiently high response speed. From the standpoint of high-speed data processing, it is expedient to select fast algorithms based on a discrete wavelet transform with the corresponding basis set functions.

The present work was devoted to assessing the possibilities and restrictions of this approach to solving the tasks of recognizing the types of motions in specially untrained persons.

The experiments were performed in a group of nine healthy volunteers. EEG signals were recorded using an Encephalan electroencephalograph in a standard 10–20 setting with additional intermediate recording electrodes, which allowed the number of signal channels to be increased to 32 (a 10–10 scheme). The pattern recognition was based on preliminarily recorded EEG signals used for the comparison of possibilities and restrictions of wavelet analysis with different basis sets. Experiments involved the recording of background brain activity (10 min) and 3-s EEG fragments accompanying accomplished motions (raising right/left arm or right/left leg). In addition, volunteers were asked to mentally reproduce (visualize) these motions and the corresponding EEG signals (reflecting visualized motor functions) were recorded. Each type of real and mentally reproduced motion was recorded no less than 40 times so as to ensure sufficient statistics, and the motions were alternated in random order so as to reduce the influence of adaptation on repeated actions.

The experimental data (EEG records) were processed using the method of multiscale wavelet analysis [20], according to which a recorded signal is expanded using a set of mirror filters, including the low-frequency $\varphi_{j,k}(t)$ and high-frequency $\psi_{j,k}(t)$ fil-

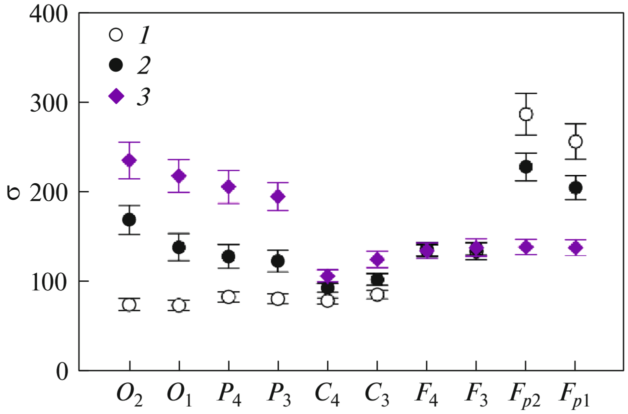

Fig. 1. Dependence of σ value on the choice of EEG recording channel (denoted according to the international 10–10 scheme). The order of electrode arrangement corresponded to the shift from the occipital to frontal region. Numbers indicate the results of calculations for (*1*) background activity, (*2*) real motions, and (*3*) imaginary motions.

ters formed by dilations and translations, respectively, of scaling function $\varphi(t)$ and wavelet $\psi(t)$ defined as

$$\varphi_{j,k} = 2^{j/2}\varphi(2^j t - k), \quad \psi_{j,k} = 2^{j/2}\psi(2^j t - k). \quad (1)$$

The basis set functions were selected from the Daubechies wavelet family [20]. The signal expansion on a given resolution level m was performed according to a fast (pyramidal) scheme as

$$x(t) = \sum_k s_{m,k}\varphi_{m,k}(t) + \sum_{j\geq m}\sum_k d_{j,k}\psi_{j,k}(t). \quad (2)$$

A quantitative criterion characterizing the variability of coefficients $d_{j,\,k}$ was the signal dispersion defined as

$$\sigma(j) = \sqrt{\frac{1}{M}\sum_{k=0}^{M-1}[d_{j,k} - \langle d_{j,k}\rangle]^2}, \quad (3)$$

where number M of expansion coefficients varies depending on scale j. As was noted in [21], the diagnostics of dynamical regimes in solving many applied problems can be provided by selecting a proper j value (e.g., 4 or 5). Taking into account those investigations and the results of our preliminary analysis of EEG signals, below we present the results of EEG signal processing for the measure of $\sigma = \sigma(5)$.

At the first stage, we solved a relatively simple task of distinguishing real and imaginary motions from the background activity. For this purpose, one type of motion (left hand raise) was selected and the results of σ calculations were compared for various arrangements of electrodes. As can be seen from Fig. 1, the choice of electrodes significantly affects the result. For example, in the occipital region (electrodes O_1 and O_2), the dispersion of wavelet coefficients for real (and even more so for imaginary) motions significantly

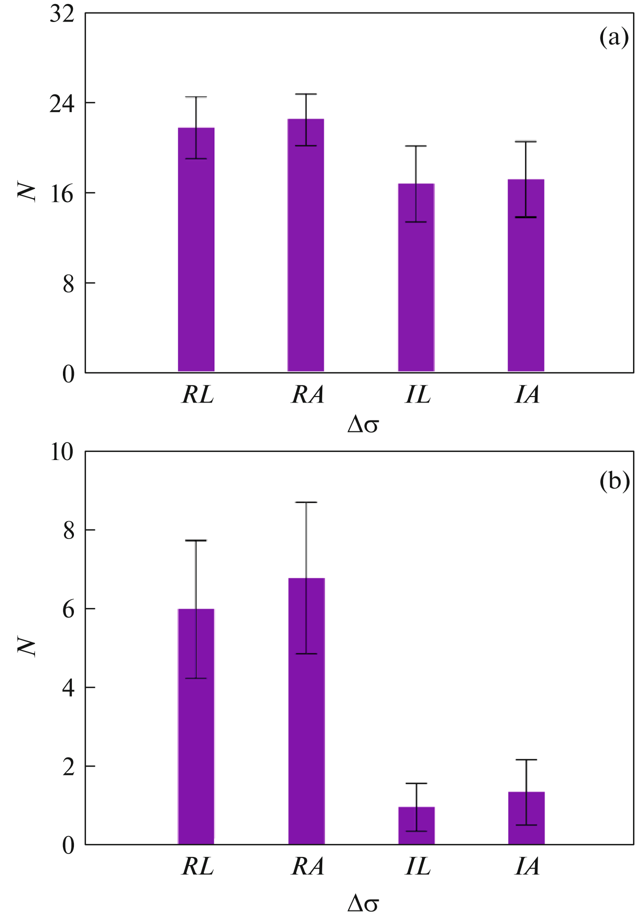

Fig. 2. Histograms of the numbers of channels used for reliably ($p < 0.01$) distinguishing the given type of motion (a) from the background activity and (b) from other types of motion. Data refer to real motions of the leg (*RL*) and arm (*RA*) and to imaginary motions of the leg (*IL*) and arm (*IA*). Calculations were performed separately for the motions of the right and left leg/arm. With allowance for the similarity of results, only averaged data are presented as mean values and standard errors.

exceeds σ value corresponding to the background activity, while electrodes situated in the frontal region (F_{p1} and F_{p2}) display the opposite effect. It should be also noted that the choice of electrodes ensuring most pronounced differences between observed EEG patterns depends on a particular volunteer.

The quality of pattern recognition can also be improved by selecting an appropriate wavelet basis set. In the present work, we have compared various basis set functions by estimating the difference between EEG patterns in terms of Student's criterion. In most experiments, the best results were obtained for a D^8 wavelet, which was selected for more detailed comparison of various experimental patterns.

At the next stage, we have analyzed the possibility of separating the types of motions and first compared EEG fragments corresponding to the motions of arms and legs. According to the data presented in Fig. 2a, these motions are recognized at comparable accuracy: reliable differences are observed in 21–22 channels out of 32 (total number). The imaginary motions are also quite reliably distinguished, although in a somewhat smaller number of channels: 16–17 out of 32. A more complicated task proved to be related to distinguishing between the type of motion: left versus right arm or leg. As can be seen from Fig. 2b, this difference is reliably detected only in 6–7 channels out of 32 for the real motions and in 1–2 channels out of 32 for the imaginary motions. At the same time, it should be noted that the number of correct channels for some volunteers was much greater than that for the other (probably, a key factor in this case can be an experience in the mental representation of motions). In particular, volunteers who repeatedly participated in such investigations showed increased number of channels with correct recognition of mental intentions.

Therefore, the apparatus of multiscale analysis can be employed for BCI development, but certain preliminary selection of channels and training of volunteers are required with allowance for individual features of participants.

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COMPLIANCE WITH ETHICAL STANDARDS

All studies involving people were conducted in accordance with principles for human experimentation as defined in the Declaration of Helsinki and International Conference on Harmonization Good Clinical Practice guidelines and later amendments or comparable ethical standards, as well as approved by the relevant institutional review boards. Informed consent was obtained from every participant in the study.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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