14.3;11.4

Changing in electroencephalography betweenness centrality with cognitive load

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A method for calculating the betweenness centrality of EEG based on wavelet bicoherence is considered. It has been established that, in the presence of cognitive load, significant betweenness centrality variations independent of the load type occur in some frequency bands.

Keywords: electroencephalogram, wavelet transform, synchronization, cognitive test.

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Investigation into the possibilities of monitoring and detecting the processes occurring in the brain under cognitive load is extremely important both for understanding the fundamental aspects of the brain functioning [1–3] and for developing the „brain–computer"interfaces [4,5]. At present, one of the most accessible tools for studying characteristics of the human brain activity is multichannel electroencephalography (EEG). EEG signals exhibit a rather complex and chaotic behavior, and their analysis typically employs various methods stemming from radiophysics and nonlinear dynamics [3,6–8], as well as artificial intelligence methods [9]. Despite significant progress in the techniques of machine learning and deep artificial intelligence, methods of radiophysics and nonlinear dynamics do not give up their positions; this is primarily caused by that they are able to explain the mechanisms of evolution of the observed regularities and their violations in patients.

One of the classes of methods actively used at present is the network analysis allowing assessment of structures emerging in the cerebral cortex activity reflected in EEG. For instance, among those methods there may be distinguished a method for assessing the betweenness centrality of EEG channels in the brain network structure simulated based on calculating wavelet bicoherence [3] in order to determine the levels of interaction between different channels. By applying this approach to processing EEG records, it is possible to quite accurately identify differences in peculiar features of the brain network structure in the state of solving cognitive problems and at rest [3]. Nevertheless, the question still remains open whether the differences in the brain network structures manifested under cognitive loads of different types will be different. This is just the issue to be solved in this work. The results obtained may be interesting both fundamentally for understanding the brain functioning in solving problems of various types and practically for assessing stability of techniques used in the „brain–computer"neural interfaces.

In this study we used EEGs recorded from clinical trial participants during various cognitive tests. The age of the volunteers ranged from 19 to 25 years; among the exclusion criteria there were obesity (body mass index > 28), chronic pain for more than six months, preexisting serious neurological disorders, psychiatric diagnoses, and also anxiety and depressive disorders (HADS (hospital anxiety and depression scale [10] > 2).

All the volunteers underwent single-type neuropsychological tests whose duration was divided into six phases (Fig 1, *a*). The first phase is resting before and after the experiment active part; the second, third and fourth phases correspond to the slow, medium and fast time of finding the Schulte matrix numbers [11]; the fifth phase is passing the test for memorizing and reproducing the points arrangement in the matrix [12]; the sixth phase is reading the test instructions to the trial subjects. All the tests were carried out using a touch monitor and special software previously created by the authors. The test protocol was generated automatically and synchronously with recording biomedical monitoring data for the trial participants. Multichannel surface EEGsignals were recorded using electroencephalograph Encephalan-EEGR-19/26 (Medicom MTD, Russia) with the sampling frequency of 250 Hz; the procedure was based on the standard monopolar recording method with two reference points and 19 active electrodes [13]; schematic diagram of the EEG electrodes arrangement is given in Fig. 1, *b*. Prior to digital processing, all the electroencephalography signals passed the preprocessing stages, namely, Gram–Schmidt filtering supplemented with electrooculography [14] for removing oculomotor artifacts and filtering based on decomposing into basic empirical modes in order to remove artificial noise and muscle artifacts [15].

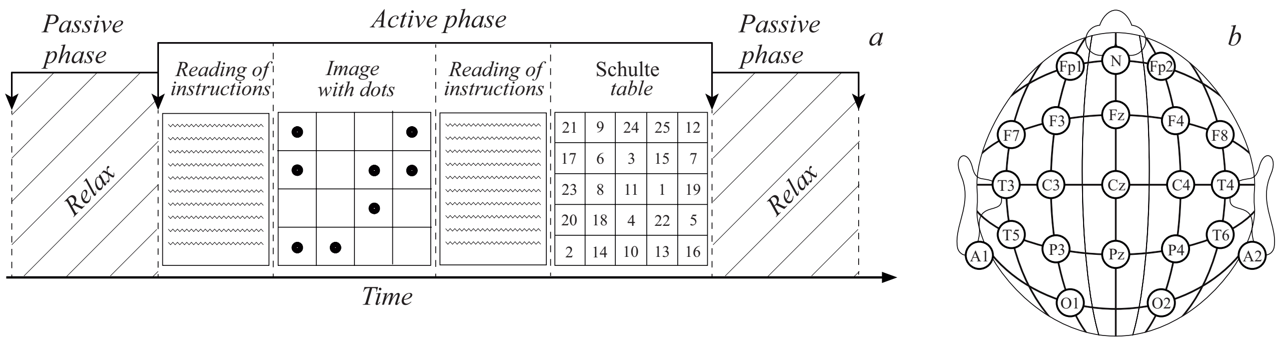

Figure 1. *a* — time-scale schedule of cognitive tests in neuropsychological experiments; *b* — arrangement of EEG electrodes.

The obtained EEG data was analyzed based on the concept described in [3]. At the first stage of analyzing the records, the method of continuous wavelet transform [14] was applied to calculate for each EEG channel $x_i(t)$, $i = 1, 2, \ldots, N$ complex coefficients

$$a_i(f,t) + jb_i(f,t) = W_i(f,t)$$
$$= \sqrt{f}\int\limits_{t-4/f}^{t+4/f} x_i(t)\left(\sqrt{f}\pi^{1/4}e^{j\omega_0 f(t-t_0)}e^{f(t-t_0)^2}/2\right)^* dt, \quad (1)$$

where j is the imaginary unit; based on coefficients (1), real and imaginary parts of wavelet bicoherence $\sigma_{i,j}(f,t)$ [16] were calculated as

$$\mathrm{Re}\left[\sigma_{i,j}(f,t)\right] = \frac{a_i(f,t)a_j(f,t)+b_i(f,t)b_j(f,t)}{\sqrt{a_i^2(f,t)+b_i^2(f,t)}\sqrt{a_j^2(f,t)+b_j^2(f,t)}},$$

$$\mathrm{Im}\left[\sigma_{i,j}(f,t)\right] = \frac{b_i(f,t)a_j(f,t)+a_i(f,t)b_j(f,t)}{\sqrt{a_i^2(f,t)+b_i^2(f,t)}\sqrt{a_j^2(f,t)+b_j^2(f,t)}}. \quad (2)$$

The modulus of the degree of coherence between two EEG leads at each experiment phase (k) was averaged over various frequency ranges under consideration and time intervals T_k corresponding to the phases of cognitive load and rest:

$$\sigma_{i,j,k}(\Delta f) = \frac{1}{T_k} \times \int\limits_{\Delta f}\sqrt{\left(\int\limits_{T_k}\mathrm{Re}[\sigma_{i,j}(f,t)]df\right)^2 + \left(\frac{1}{T_k}\int\limits_{T_k}\mathrm{Im}\left[\sigma_{i,j}(f,t)\right]dt\right)^2}\,df. \quad (3)$$

In this work, seven frequency ranges were chosen for analyzing the EEG signals: $\Delta f_1 \in [0.5; 1.5]$ Hz, $\Delta f_2 \in [1.0; 4.0]$ Hz, $\Delta f_3 \in [4.0; 8.0]$ Hz, $\Delta f_4 \in [8.0; 12.0]$ Hz, $\Delta f_5 \in [12.0; 20.0]$ Hz, $\Delta f_6 \in [15.0; 25.0]$ Hz and $\Delta f_7 \in [20.0; 30.0]$ Hz. As a result, $N \times N$ matrices reflecting information on the degree of phase coherence between all $N = 19$ EEG leads were obtained for each phase of the experiment and each frequency range. Quantity $\sigma_{i,j,k}(\Delta f)$ takes values from „0" to „1" while „0" designates the absence of phase coherence and „1" designates complete phase coherence; therewith, $\sigma_{i,i,k}(\Delta f) = 1 \forall k, \forall \Delta f$.

Then, in order to assess the connectivity structure in EEG leads, the phase-coherent matrices obtained for each frequency range were analyzed using a measure for assessing the centrality of connections [3,17]. This measure created on the basis on calculating the shortest paths between the network nodes allows estimating centrality for each of them as a value proportional to the number of shortest paths passing through this node. To calculate the node centrality, let us pass to considering a weighted plot whose N nodes correspond to the EEG leads, while weights $w_{i,j}$ of edges connecting the ith and jth nodes should be the lower, the higher is the phase coherence between these edges: $w_{i,j,k,\Delta f} = 1 - \sigma_{i,j,k}(\Delta f)$. Then the centrality for each ith EEG lead can be calculated as

$$\tilde{g}_{i,k,\Delta f} = \sum_{i \neq j \neq l} \Lambda^i_{j,l}/\Lambda_{j,l}, \quad (4)$$

where $\Lambda^i_{j,l}$ is the number of shortest paths between nodes j and l passing through the i-th node, and $\Lambda_{j,l}$ is the total number of shortest paths between nodes j and l; k indicates the experiment phase, Δf is the frequency range. For each phase and each range, obtain $N = 19$ values of $\tilde{g}_i$ and normalize them:

$$g_{i,k,\Delta f} = \frac{\tilde{g}_{i,k,\Delta f}}{\sum\limits_{\forall \Delta f}\sum\limits_{i=1}^{N}\tilde{g}_{i,k,\Delta f}}. \quad (5)$$

Centrality degrees $g_{i,k,\Delta f}$ were calculated for all the trial participants at all six phases of the experiment in the above-specified frequency ranges. To continue the analysis, parameters $g_{i,k,\Delta f}$ were grouped according to the experiment phases and regions of EEG electrodes location (leads of the right and left hemispheres, motor zone areas) and visualized as standard range box plots [18] (Fig. 2, *a*–*c*).

Ranges Δf_2, Δf_3, Δf_6 and Δf_7 exhibit no significant differences in centrality between different phases of the experiment. In the Δf_1 range (δ rhythm, Fig. 2, *a*), centrality at the phases with cognitive load increases with

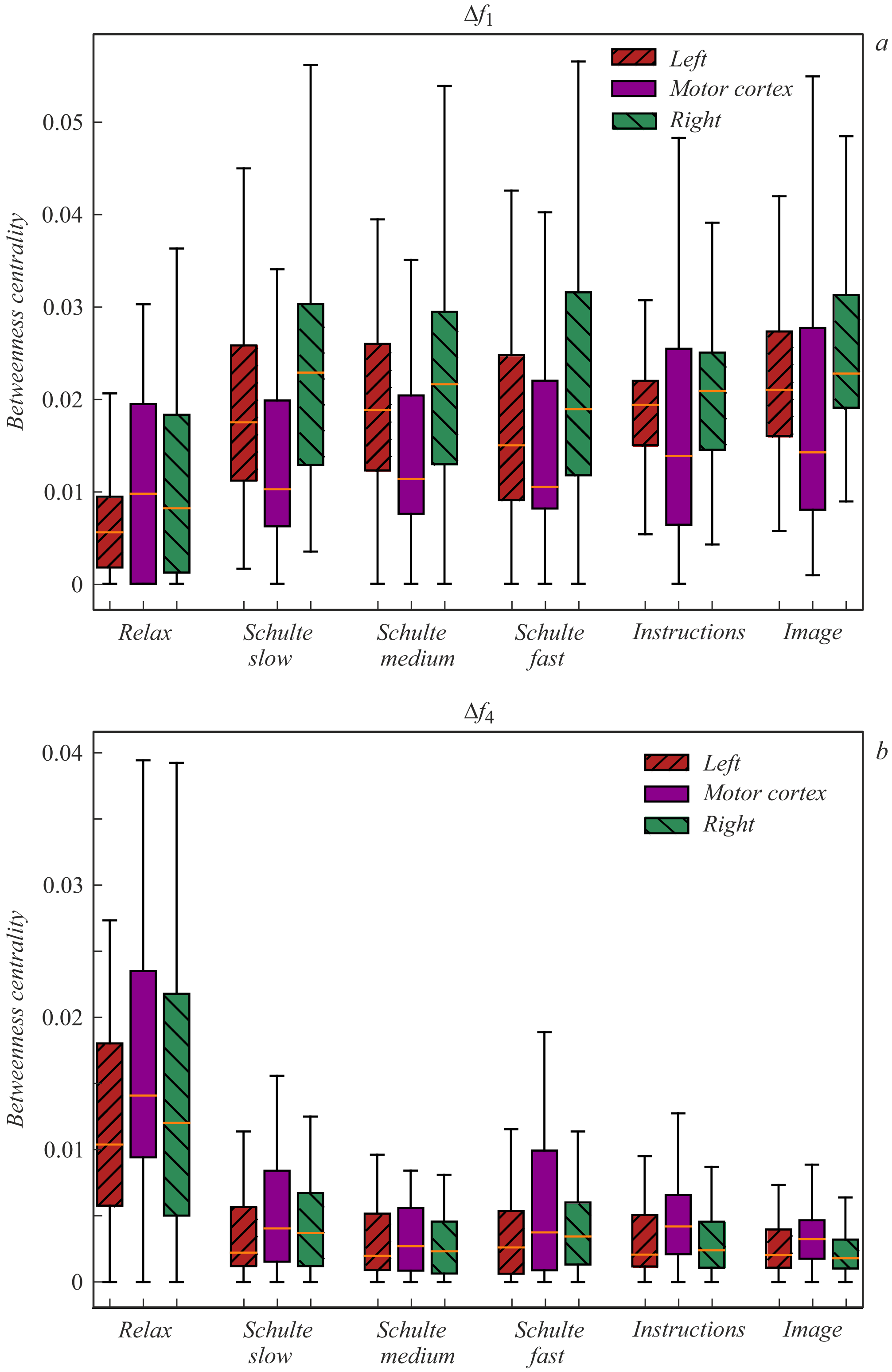

Figure 2. Box plots of the range of betweenness centrality $g_{i,k}$ for all the trial subjects at all the experiment phases in frequency ranges $\Delta f_1 \in [0.5; 1.5]$ Hz (*a*), $\Delta f_4 \in [8.0; 12.0]$ Hz (*b*) and $\Delta f_5 \in [12.0; 20.0]$ Hz (*c*). The median (orange line), lower and upper quartiles, and confidence interval are shown. The horizontal axis represents phases of the experiment. Green color corresponds to the right hemisphere EEG leads, red color is for the left hemisphere, violet color is for the motor cortex region. The colored figure is given in the electronic version of the paper.

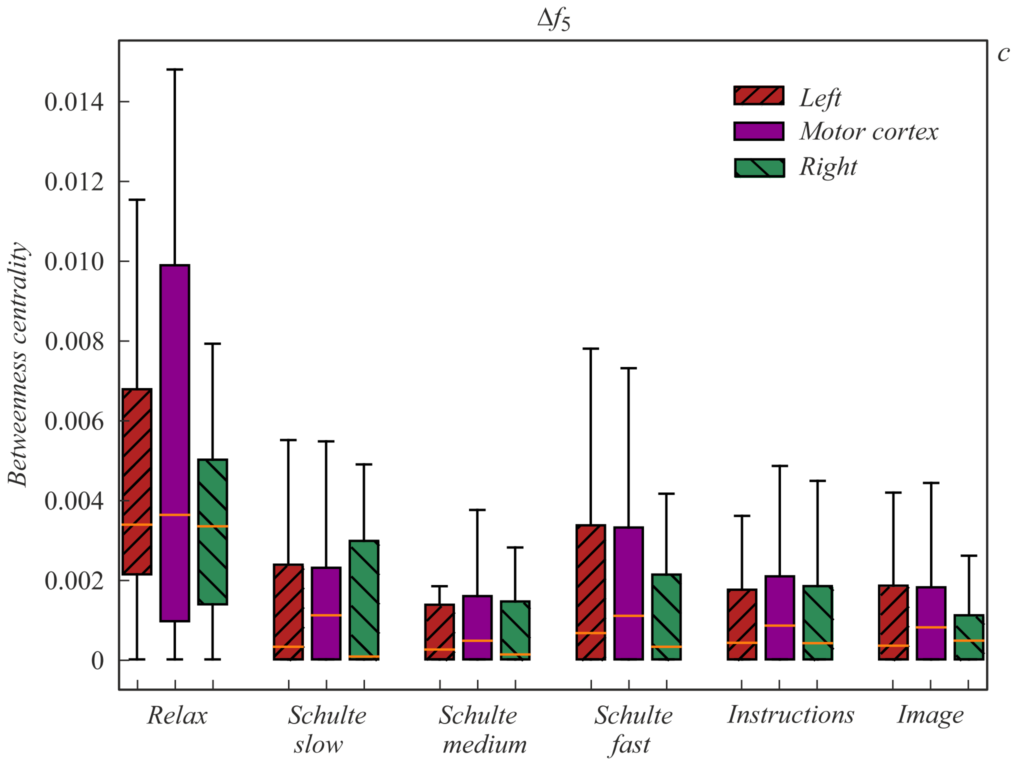

Fig. 2 (*continued*).

respect to that at the phases of rest. This variation is most pronounced when signals from the right and left hemispheres are considered. When considering leads from the motor cortex region only, the δ range does not exhibit noticeable variations in centrality.

In the Δf_4 (Fig. 2, b) and Δf_5 (Fig. 2, c) ranges corresponding to the α— and βrhythms, respectively, centrality at the phases of cognitive load is considerably lower than at the phase of rest. The difference in centralities is most clearly manifested in the α range (Fig. 2, b) both in the motor cortex area and in other leads.

Note that the type of cognitive load and speed of solving the problem do not affect the degree of centrality: in all the considered ranges, phases with cognitive load overlap with the ranges of values of the first and third quartiles. Thereat, the phase of rest intersects only with the confidence intervals. Reliability of differences in centralities at the rest stages (passive phase) and cognitiveload stages (active phase) was high: $p < 0.05$ in the Δf_4, Δf_5 frequency ranges and $p < 0.01$ in frequency range Δf_1 in accordance with the Mann–Whitney criterion [19]. However, since multiple comparisons are to be performed (three zones of brain activity), it is necessary to take into account the Bonferroni correction [20], which reduces reliability of the differences to frequency range Δf_1 only.

Thus, the approach proposed here allows constructing a classifier able to distinguish the state of rest from the state of solving any cognitive task by assessing the degree of centrality. Such a classifier may be used, for example, in developing neural interfaces „brain–computer“ as a test system determining whether a human is currently solving a certain problem or is resting and ignoring the allotted task. At the same time, it is impossible to distinguish the loads from different human cognitive functions.

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Compliance with Ethical Standards

All the human trials comply with Ethical Standards of the institutional and/or national research ethics committee, as well as with Declaration of Helsinki (1964) and its subsequent amendments or matched ethical norms. An informed voluntary consent was obtained from each trial participant.

Conflict of interests

The authors declare that they have no conflict of interests.

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