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Source-level analysis of brain activity in the process of learning and retrieving new information

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***Abstract*—In this paper, we discovered the increase in EEG power in the theta frequency range in the occipital cortex during a visual analysis of new information and the power decrease in the alpha range in the temporal lobe during retaining information. The revealed increase in theta power correlates with the response time and errors rate. The alpha power correlates with response time. Summarizing the above, the detected cluster of theta-activity during information perception may reflect the increased concentration of attention.**

***Index Terms*—Electroencephalography, source localization, cognitive activity analysis, efficiency of information processing, working memory, learning information, retrieving information**

I. Introduction

Currently, the urgent tasks of cognitive sciences are associated with the search for opportunities to increase the efficiency of retaining new information through intelligent systems to optimize the educational load, taking into account the individual psychophysiological characteristics of students, their cognitive state, and characteristics of memory [1]–[3]. This direction is actively developing in world science [4]. A bulk of works aim to identify neurophysiological markers that characterize the efficiency of the human brain in the process of perception and assimilation of information and the efficiency of memory [5]–[7]. In these works, the features of the time-frequency and space-time structure of brain activity signals are determined using artificial intelligence methods and statistical analysis [8]–[14]. However, as a rule, the specific neurophysiological mechanisms of neural activity that determine the formation of the corresponding patterns are not discussed in detail. As a result, the developed approaches are characterized by a strong binding to a specific subject and instability of operation due to the variability of the properties of neural activity under the influence of external and internal factors. In addition, the mechanisms that determine the relationship between the cognitive state of a person and the efficiency of memory in the process of retaining new information remain poorly understood [15].

Here, we investigate the mechanisms of the neural activity responsible for the relationship between the cognitive state of a person in the learning process and the effectiveness of assimilation of educational material.

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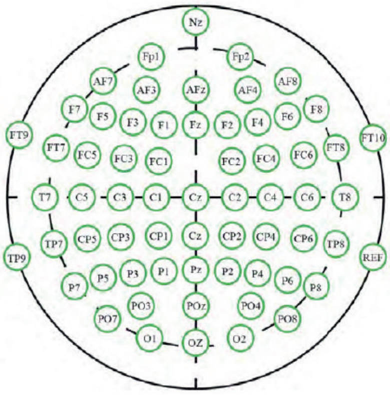

Fig. 1. Arrangement of EEG electrodes on the subject's head based on scheme 10-10; Nz – ground, REF – reference.

II. Materials and methods

The experimental design was based on the Sternberg paradigm. This test allows one to explore information-processing mechanisms in short-term memory [16]. The main part of the experiment begins and ends by recording the background activity for 60 s and consists of four blocks of tasks. Each block in the main part consists of 72 trials; within a trial, it is necessary to complete the task in the form of the Sternberg test.

The experimental studies involved 17 student volunteers (11 males and 6 females, mean age – 20 years) — nonsmokers, not taking medications, not involved in professional sports, with normal or restored to normal vision, without a history of neurophysiological diseases. Within 48 hours before the experiment, all volunteers were asked to adhere to a healthy lifestyle: ensure at least 8 hours of sleep, eliminate alcohol consumption, eliminate or limit consumption of caffeine-containing foods, and avoid excessive physical exertion. The volunteers were familiarized with the experimental procedure in advance and were aware of the possible inconveniences associated with participating in the experiment. Also, they had the opportunity to ask questions of interest and get satisfactory answers to them. Each volunteer completed and signed an informed consent form for participation in the experiment. All experimental works were carried out in accordance with the requirements of the Declaration of Helsinki and approved by the Ethics Commission of Innopolis University.

The experiment was carried out as follows. The subject sat in a specialized chair for carrying out neurophysiological experiments. There was a monitor on the table in front of him (distance from the screen to the eyes 90 cm; monitor resolution 1920 x 1080). A mouse and two one-button remote controls were used as input devices. The monitor was used to demonstrate tests and tasks, while input devices were used to record the subject's responses. The duration of each experiment was about 60-65 minutes. During the experiment, the electrical activity of the brain was recorded using actiCHamp electroencephalograph (Brain Products, Germany). EEG signals were recorded from 63 channels following the 10-10 scheme (see Fig. 1). The ground (Nz) was located at the location of the Fpz electrode, and the reference electrode (REF) was placed behind the right ear. For EEG registration, active Ag/AgCl electrodes ActiCAP were used, which were located on the scalp surface in the sockets of a special EasyCAP cap. The scalp was pretreated with NuPrep abrasive gel to improve signal quality and provide better conductivity, and then the electrodes were positioned using SuperVisc conductive gel.

In the experiments, EEG signals were recorded with a sampling rate of 1 kHz and filtered using: bandpass (1-70 Hz) and notch (49.5-50.5 Hz) filters. The bandpass filter limits the considered frequency range on the EEG signals and removes low-frequency and high-frequency activities not associated with the EEG. The notch filter removes 50 Hz interference from the power grid. Eyes blinking and heartbeat artifacts removal was performed by the Independent Component Analysis (ICA). Data was then inspected manually and corrected for remaining artifacts.

The work investigates the influence of task complexity, expressed in the amount of processed information, on the cognitive mechanisms of material learning. The amount of information was measured in the number of symbols (letters) that the subject had to remember. According to the number of memorized symbols, we divided the difficulty into three levels: Low, Moderate, and High. At first, we studied the influence of task complexity on behavioral assessments of the effectiveness of information processing: the time that the subject spent retrieving information from memory when passing the test (response time, RT) and the percentage of erroneous answers (errors rate, ER). We used repeated-measures ANOVA for the analysis.

For EEG analysis, we considered three types of trials. The first type (TOI1) had a duration of 1.5 seconds and was time-locked to the moment of information presentation. In this case, we analyze the effect of task complexity on neural activity associated with processing sensory information. The second type of trial (TOI2) had a duration of 3 seconds and was time-locked to the moment of disappearance of the material. Here we study the effect of task complexity on neural activity associated with learning (placement of information in working memory). The third type of trial (TOI3) had a duration of 2 seconds and was time-locked to the moment of the presentation of the test card. In this case, we investigate the influence of task complexity on neural activity associated with retrieving information from working memory.

To identify the mechanisms of the neural activity responsible for the relationship between the cognitive state of a person and the efficiency of memorization, we localized the sources of neural activity in frequency bands of interest (FOI) corresponding to the time-frequency clusters identified at the sensor-level [17]. To this end, the exact low-resolution electrical tomography (eLORETA) method [18] was used, which works in the time domain. The Colin27 brain MRI template [19] was used to create a head model based on the boundary element method (BEM) with three tissue types (brain, skull,

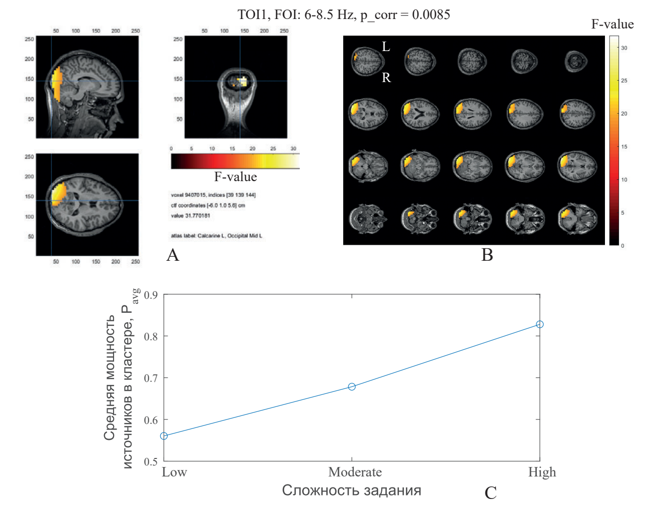

Fig. 2. Distribution of the F-statistic value in 3 orthogonal sections (A) and twenty head slices in a single plane (B) in the cluster identified for TOI1 in the frequency range 6-8.5 Hz, in which the power of the sources significantly differs between 3 levels of task difficulty. The cross in Figure A indicates the area with the highest F-statistic. (C) Dependence of the power of the sources in the identified cluster, averaged over all subjects, on the task complexity.

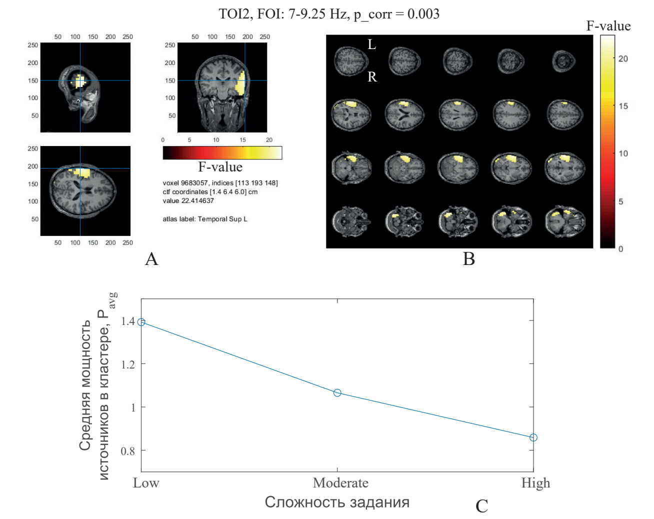

Fig. 3. Distribution of the F-statistic value in 3 orthogonal sections (A) and twenty head slices in a single plane (B) in the cluster identified for TOI2 in the frequency range 7-9.25 Hz, in which the power of the sources significantly differs between 3 levels of task difficulty. The cross in Figure A indicates the area with the highest F-statistic. (C) Dependence of the power of the sources in the identified cluster, averaged over all subjects, on the task complexity.

and scalp) [20]. As a result of applying the eLORETA method for each condition, the power distributions of the activity of the sources in the brain on a three-dimensional grid with 11930 nodes (voxels) were obtained. We used the brain atlas with automated anatomical labeling (AAL) [21] to correlate the location of the sources with the anatomical regions of the brain. Note that the powers of the sources were averaged over the corresponding time interval of interest (TOI). To reduce the variability of the obtained power distributions between the subjects, they were normalized to the power of the sources at rest (the so-called "baseline correction") in the form of a relative change. The statistical F-test was used to compare the obtained power distributions of the sources corresponding to different conditions. The problem of multiple comparisons was solved using a cluster permutation test with Monte Carlo randomization [22]. To analyze the direction of the effect between conditions, we averaged the power of the sources over the voxels included in the corresponding identified cluster.

We used FieldTrip software for all processing [23]. Correlation analysis was carried out using the repeated-measures correlations method [24]. For each case, the correlation coefficient, the value of the statistics, and the confidence interval boundaries were calculated.

III. Results

For TOI1, we found a significant cluster in the 6-8.5 Hz frequency range with a significance level of 0.0085 (see Fig. 2A, B). The cross in Fig. 2A indicates the zone with the highest F-statistic, located in the left hemisphere in the vicinity of the visual sulcus (Calcarine L) and the middle occipital gyrus (Occipital Mid L). The cluster includes the following areas of the brain in the left hemisphere: Calcarine L, Cuneus L, lingual gyrus (Lingual L), superior occipital gyrus (Occipital Sup L), Occipital Mid L, inferior occipital gyrus (Occipital Inf L), fusiform gyrus (Fusiform L), middle temporal gyrus (Temporal Mid L), inferior temporal gyrus (Temporal Inf L), and cerebellar zones. The power of the sources in this cluster increased with the increasing complexity of the task (see Fig. 2C).

For TOI2, we found a significant cluster in the 7-9.25 Hz frequency range with a significance level of 0.003 (see Fig. 3A, B). The cross in Fig. 3A indicates the zone with the highest F-statistic, located in the left hemisphere in the vicinity of the superior temporal gyrus (Temporal Sup L). The cluster includes the following areas of the brain in the left hemisphere: precentral gyrus (Precentral L), opercular part of the inferior frontal gyrus (Frontal Inf Oper L), rolandic operculum (Rolandic Oper L), insular lobe (Insula L), amygdala (Amygdala L), middle occipital gyrus (Occipital Mid L), inferior occipital gyrus (Occipital Inf L), postcentral gyrus (Postcentral L), supra-marginal gyrus (SupraMarginal L), Heschl L, superior temporal gyrus (Temporal Sup L), middle temporal gyrus (Temporal Mid L), inferior temporal gyrus (Temporal Inf L), and the cerebellar zone. The power of the sources in this cluster decreased with the increasing complexity of the task (see Fig. 3C). We identified no significant clusters for TOI3.

We obtained the following results from the analysis of correlations between the efficiency of information processing, expressed in response time (RT) and errors rate (ER), and patterns of neural activity. The response time (RT) positively correlates with the power of sources of neural activity in the theta range in TOI1: $r(29) = 0.61$, $p = 0.00022$, 95% confidence interval: $[0.3220.801]$. The RT negatively correlates with the power of neural activity sources in the alpha range in TOI2: $r(29) = -0.518$, $p = 0.00282$, 95% confidence interval: $[-0.743 - 0.187]$. The error rate (ER) positively correlates with the power of sources of neural activity in the theta range in TOI1: $r(29) = 0.557$, $p = 0.0011$, 95% confidence interval: $[0.2390.767]$. The ER does not correlate with the power of sources of neural activity in the alpha range in TOI2: $r(29) = -0.331$, $p = 0.068$, 95% confidence interval $[-0.6220.040]$.

IV. Conclusion

We revealed that, in terms of neural activity, there is an increase in EEG power in the theta range in the occipital cortex during a visual analysis of information (TOI1), as well as a decrease in the power in the alpha range in the temporal lobe during memorization (TOI2). The increase in theta power in TOI1 correlates with the RT and ER. The alpha power at TOI2 correlates with RT but is not correlated with ER. Summarizing the above, the detected cluster of theta-activity during information perception may reflect the increased concentration of attention. According to the results of the correlation analysis, this indicator determines the effectiveness of the subject during the subsequent retrieving of information from memory, both in terms of RT and ER.

V. Acknowledgment

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References

[1] G. Knyazev, E. Merkulova, A. Savostyanov, A. Bocharov, and A. Saprigyn, "Personality and eeg correlates of reactive social behavior," *Neuropsychologia*, vol. 124, pp. 98–107, 2019.

[2] L.-W. Ko, O. Komarov, W. D. Hairston, T.-P. Jung, and C.-T. Lin, "Sustained attention in real classroom settings: An eeg study," *Frontiers in human neuroscience*, vol. 11, p. 388, 2017.

[3] T. Bukina, M. Khramova, and S. Kurkin, "Modern research on primary school children brain functioning in the learning process," *Izvestiya VUZ. Applied Nonlinear Dynamics*, vol. 29, no. 3, pp. 449–456, 2021.

[4] V. Maksimenko, A. Kuc, N. Frolov, S. Kurkin, and A. Hramov, "Effect of repetition on the behavioral and neuronal responses to ambiguous necker cube images," *Scientific Reports*, vol. 11, no. 1, pp. 1–13, 2021.

[5] P. Aricò, G. Borghini, G. Di Flumeri, N. Sciaraffa, and F. Babiloni, "Passive bci beyond the lab: current trends and future directions," *Physiological measurement*, vol. 39, no. 8, p. 08TR02, 2018.

[6] S. A. Kurkin, V. V. Grubov, V. A. Maksimenko, E. N. Pitsik, M. V. Hramova, and A. E. Hramov, "System for monitoring and adjusting the learning process of primary schoolchildren based on the eeg data analysis," *Information and Control Systems*, no. 5, pp. 50–61, 2020.

[7] A. A. Badarin, V. V. Skazkina, and V. V. Grubov, "Studying of human's mental state during visual information processing with combined eeg and fnirs," in *Saratov Fall Meeting 2019: Computations and Data Analysis: from Nanoscale Tools to Brain Functions*, vol. 11459. International Society for Optics and Photonics, 2020, p. 114590D.

[8] P. Chholak, A. N. Pisarchik, S. A. Kurkin, V. A. Maksimenko, and A. E. Hramov, "Phase-amplitude coupling between mu-and gamma-waves to carry motor commands," in *2019 3rd School on Dynamics of Complex Networks and their Application in Intellectual Robotics (DCNAIR)*. IEEE, 2019, pp. 39–45.

[9] S. Kurkin, E. Pitsik, and N. Frolov, "Artificial intelligence systems for classifying eeg responses to imaginary and real movements of operators," in *Saratov Fall Meeting 2018: Computations and Data Analysis: from Nanoscale Tools to Brain Functions*, vol. 11067. International Society for Optics and Photonics, 2019, p. 1106709.

[10] S. Kurkin, P. Chholak, V. Maksimenko, and A. Pisarchik, "Machine learning approaches for classification of imaginary movement type by meg data for neurorehabilitation," in *2019 3rd School on Dynamics of Complex Networks and their Application in Intellectual Robotics (DCNAIR)*. IEEE, 2019, pp. 106–108.

[11] S. Kurkin, A. Badarin, V. Grubov, V. Maksimenko, and A. Hramov, "The oxygen saturation in the primary motor cortex during a single hand movement: functional near-infrared spectroscopy (fnirs) study," *The European Physical Journal Plus*, vol. 136, no. 5, pp. 1–9, 2021.

[12] P. Chholak, S. A. Kurkin, A. E. Hramov, and A. N. Pisarchik, "Event-related coherence in visual cortex and brain noise: An meg study," *Applied Sciences*, vol. 11, no. 1, p. 375, 2021.

[13] S. A. Kurkin, E. N. Pitsik, V. Y. Musatov, A. E. Runnova, and A. E. Hramov, "Artificial neural networks as a tool for recognition of movements by electroencephalograms." in *ICINCO (1)*, 2018, pp. 176–181.

[14] S. Kurkin, V. Y. Musatov, A. E. Runnova, V. V. Grubov, T. Y. Efremova, and M. O. Zhuravlev, "Recognition of neural brain activity patterns correlated with complex motor activity," in *Saratov Fall Meeting 2017: Laser Physics and Photonics XVIII; and Computational Biophysics and Analysis of Biomedical Data IV*, vol. 10717. International Society for Optics and Photonics, 2018, p. 107171J.

[15] A. E. Hramov, N. S. Frolov, V. A. Maksimenko, S. A. Kurkin, V. B. Kazantsev, A. N. Pisarchik *et al.*, "Functional networks of the brain: from connectivity restoration to dynamic integration," *Physics-Uspekhi*, vol. 64, no. 6, 2021.

[16] L. Pelosi, M. Hayward, and L. Blumhardt, "Is "memory-scanning" time in the sternberg paradigm reflected in the latency of event-related potentials?" *Electroencephalography and Clinical Neurophysiology/Evoked Potentials Section*, vol. 96, no. 1, pp. 44–55, 1995.

[17] S. Kurkin, A. Hramov, P. Chholak, and A. Pisarchik, "Localizing oscillatory sources in a brain by meg data during cognitive activity," in *2020 4th International Conference on Computational Intelligence and Networks (CINE)*. IEEE, 2020, pp. 1–4.

[18] R. D. Pascual-Marqui, D. Lehmann, M. Koukkou, K. Kochi, P. Anderer, B. Saletu, H. Tanaka, K. Hirata, E. R. John, L. Prichep *et al.*, "Assessing interactions in the brain with exact low-resolution electromagnetic tomography," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 369, no. 1952, pp. 3768–3784, 2011.

[19] C. J. Holmes, R. Hoge, L. Collins, R. Woods, A. W. Toga, and A. C. Evans, "Enhancement of mr images using registration for signal averaging," *Journal of computer assisted tomography*, vol. 22, no. 2, pp. 324–333, 1998.

[20] M. Fuchs, J. Kastner, M. Wagner, S. Hawes, and J. S. Ebersole, "A standardized boundary element method volume conductor model," *Clinical neurophysiology*, vol. 113, no. 5, pp. 702–712, 2002.

[21] N. Tzourio-Mazoyer, B. Landeau, D. Papathanassiou, F. Crivello, O. Etard, N. Delcroix, B. Mazoyer, and M. Joliot, "Automated anatomical labeling of activations in spm using a macroscopic anatomical parcellation of the mni mri single-subject brain," *Neuroimage*, vol. 15, no. 1, pp. 273–289, 2002.

[22] E. Maris and R. Oostenveld, "Nonparametric statistical testing of eeg-and meg-data," *Journal of neuroscience methods*, vol. 164, no. 1, pp. 177–190, 2007.

[23] R. Oostenveld, P. Fries, E. Maris, and J.-M. Schoffelen, "Fieldtrip: open source software for advanced analysis of meg, eeg, and invasive electrophysiological data," *Computational intelligence and neuroscience*, vol. 2011, 2011.

[24] J. Z. Bakdash and L. R. Marusich, "Repeated measures correlation," *Frontiers in psychology*, vol. 8, p. 456, 2017.