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Biomarkers of brain activity for the performance evaluation in the process of solving cognitive tasks

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***Abstract*—In this paper, we analyze the brain activity during the execution by the subject of simple cognitive tasks associated with visual attention and symbol perception. We obtain biomarkers of brain activity in the process of solving cognitive tasks. These biomarkers make it possible to relate the quality and speed of execution of the tasks offered to the subject with the brain's activity of the cortical network. We use a combination of time-frequency and statistical analysis to calculate activity characteristics. The results obtained can be used to develop neural interfaces for training attention and adjusting the learning process.**

***Index Terms*—Biomarkers,EEG, brain activity, cognitive task**

I. Introduction

The direction of monitoring human cognitive functions in the learning process is actively developing in world science. There are many works aimed at identifying neurophysiological markers characterizing the efficiency of the human brain in the process of perception and assimilation of information, as well as the efficiency of memory [1]–[8]. Mostly, the features of time-frequency and spatial-temporal structures of signals of brain activity are determined using artificial intelligence methods and statistical analysis (reduction of dimension, feature extraction, clustering, etc.) [9]–[14]. But the developed approaches are characterized by a strong binding to a specific subject, as well as instability of operation due to the variability of the properties of neural activity under the influence of external and internal factors.

The urgency of this problem is connected with the search for opportunities to increase the efficiency of the educational process (the efficiency of mastering new information) by using intelligent systems to optimize the educational load, taking into account the individual psychophysiological characteristics of students, their cognitive state and characteristics of memory.

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One of the efficient method to study brain activity is obtain experimental data by using EEG [15]–[18], MEG [5], [19]–[21], [21] or fNIRS [22]–[24]. Another way is numerical simulation of neural network activity by using different neuron's models [25]–[29] which allows to investigate the processes of inter-neuron interaction or collective neural dynamics [30]. EEG-based research on the analysis of brain activity seems to be especially promising. First of all, this is due to the fact that EEG, being a relatively inexpensive, affordable, easy-to-use and safe technology, allows obtaining objective information about the brain's work with good time resolution [31]. Moreover, when using EEG, preliminary analysis and optimization usually allows to significantly reduce the number of electrodes, as well as the duration of recordings of EEG signals when solving a specific problem [32]. For example, in [33], it was shown that the state of the subject upon perception of an ambiguous visual stimulus can be identified with high accuracy using signals recorded with only two EEG channels. The use of EEG for an objective analysis of the cognitive characteristics of students and personalization of the learning process through the implementation of feedback based on the data obtained will significantly improve the quality of the educational process and the efficiency of learning new material [31].

Here, we analyze the brain activity during the performance by the subject of simple cognitive tasks associated with visual attention and symbol perception. We obtain biomarkers of brain activity in the process of solving cognitive tasks. These biomarkers make it possible to relate the quality and speed of performance of the tasks offered to the subject with the brain's activity of the cortical network. We use a combination of time-frequency and statistical analysis to calculate activity characteristics. The results obtained can be used to develop neural interfaces for training attention and adjusting the learning process.

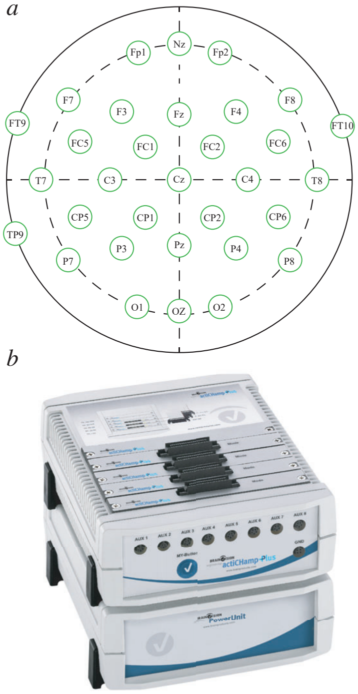

Fig. 1. (a) Electrode locations of International 10-10 system for EEG recording. (b) The ActiCHamp electroencephalograph manufactured by Brain Products.

II. Materials and Methods

The experimental studies involved 10 schoolchildren aged 7 to 10 years without neuropsychological diseases, who did not take medication. The children and their parents were familiarized in advance with the procedure of the experiment and the possible inconveniences caused by it had the opportunity to ask questions of interest and get satisfactory answers to them. Each of the subjects' parents completed and signed an informed consent form for participation in the experiment. All experimental work was 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 was sitting in a comfortable chair, and a tablet was placed on the table in front of him (distance from the screen to the eyes $\approx$ 30-40 cm). The tablet was used both for demonstrating test questions and for recording answers with a stylus. The duration of each individual experiment was $\approx$10-15 minutes, depending on the speed of the tasks performed by the subjects.

During the experiment, the activity of the brain was recorded using electroencephalography (EEG). For this, the equipment at the disposal of the Laboratory of Neuroscience and Cognitive Technologies was used. EEG signals provide insight into the electrical activity of the brain.

The EEG activity was recorded using an actiCHamp electroencephalograph manufactured by Brain Products, Germany (see 1). EEG signals were recorded for 31 channels in accordance with the 10-10 scheme (see $1a$). The ground was located at the site of the Fpz electrode, and the reference electrode 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. To improve signal quality and provide better conductivity, the scalp was pretreated with NuPrep abrasive gel, and then the electrodes were positioned using SuperVisc conductive gel. During the experiment, the conductivity values were monitored at each of the EEG electrodes. Typically, the values were 25 $< k\Omega$ which is sufficient for the correct operation of active EEG electrodes.

The well-known Schult table was considered as a task (see $2a$). The completion of this task allows determining the effectiveness of the test subject's work and his ability to work, as well as resistance to external distractions. By default, the Schulte table is a 5x5 matrix with randomly located numbers from 1 to 25. By default, the subject should select numbers from 25 to 1 in the table in descending order by clicking on them on the tablet. The system registers time intervals between two consecutive clicks on adjacent numbers. Each test subject completed N = 5 Schulte tables, the execution of 1 table took from 50 to 90 s. Between the tables, there was a short break of 10–20 s.

In the course of the experimental work, EEG signals were recorded with a sampling frequency of 1000 Hz and filtered using a bandpass filter (1-70 Hz) and a notch filter (49.5-50.5 Hz). The bandpass filter serves to limit the studied range on the EEG signals and remove low-frequency activity associated, for example, with respiration, and high-frequency components that appear when the electrodes are poorly connected, their displacement, various external influences, etc. Studies show that when studying the cognitive activity of the brain, such frequency ranges as delta (1-4 Hz), theta (4-8 Hz), alpha (8-14 Hz), beta 1 and 2 (15-40 Hz)), gamma (40-60 Hz). Thus, the frequency range of the studied EEG signals after filtering makes it possible to explore all the listed ranges. The notch filter serves to remove the 50 Hz pickup from the mains, which inevitably appears on the EEG signals regardless of the conditions of the experiment.

Thus, filtering EEG signals allows you to get rid of many interferences, however, various physiological artifacts caused, for example, by cardiac rhythms, eye movements, facial and neck muscles, etc., are also a problem in the time-frequency analysis of EEG signals. The main difficulty here is that the frequency range of most physiological artifacts overlaps with the useful frequency ranges of the EEG signal. In this case, various methods are used related to the decomposition of the EEG signal (for example, Gram-Schmidt orthogonalization). One of the most popular methods in the field is Independent Component Analysis (ICA). When applied to EEG signals, ICA makes it possible to decompose the entire EEG data set into a number of independent components. Obviously, the movements of the eyeball or neck muscles are independent of the electrical activity of the brain; therefore, the component containing the artifacts should also be independent of the other components containing the EEG signals.

5	16	11	6	18
24	9	7	12	14
3	4	10	25	1
23	2	15	21	19
20	17	22	8	13

Fig. 2. Typical example task with a Schulte table from part of the test. The arrows show the sequence of the necessary choices for the correct solution.

As part of the work, the ICA method was applied to the recorded EEG signals - by decomposing the EEG signals into a set of components, removing the component with artifacts, and resumming the remaining components, one can obtain the original EEG data set with the removed artifacts.

We have analyzed the EEG signals using the continuous wavelet transform which is now widely used in neuroscience and neurophysiology. The instant wavelet energy spectrum $E^n(f,t) = \sqrt{W_n(f,t)^2}$ was calculated for each EEG channel $X_n(t)$ in the frequency range $f \in [1, 70]$ Hz. Here, $W_n(f,t)$ is the complex-valued wavelet coefficients calculated as

$$W_n(f,t) = \sqrt{f} \int_{-\infty}^{+\infty} X_n(t)\psi^*(f,t)dt, \quad (1)$$

where $n = 1, ..., N$ is the EEG channel number ($N = 31$ being the total number of channels used for the analysis) and "*" defines the complex conjugation. The mother wavelet function $\psi(f,t)$ is the Morlet wavelet often used for the analysis of neurophysiological data, defined as

$$\psi(f,t) = \sqrt{f}\pi^{1/4} e^{j\omega_0 f(t-t_0)} e^{f(t-t_0)^2/2}, \quad (2)$$

where $\omega_0 = 2\pi$ is the central frequency of the mother Morlet wavelet.

In this paper, we calculate separately the average energy in the alpha(8–13 Hz) and beta(15–40 Hz) bands during the execution of each of the tables.

$$E^n_{\alpha,\beta,\Delta t_1,\Delta t_2} = \frac{1}{\Delta f \Delta t} \int_{t\in\Delta t_1,\Delta t_2} \int_{f\in\alpha,\beta} E^n(f,t)df. \quad (3)$$

For each presentation of the table, we calculate the following characteristic D(t), which demonstrates the ratio of average energies in the alpha and beta bands:

$$D(k) = \frac{E^n_\beta}{E^n_\alpha} \quad (4)$$

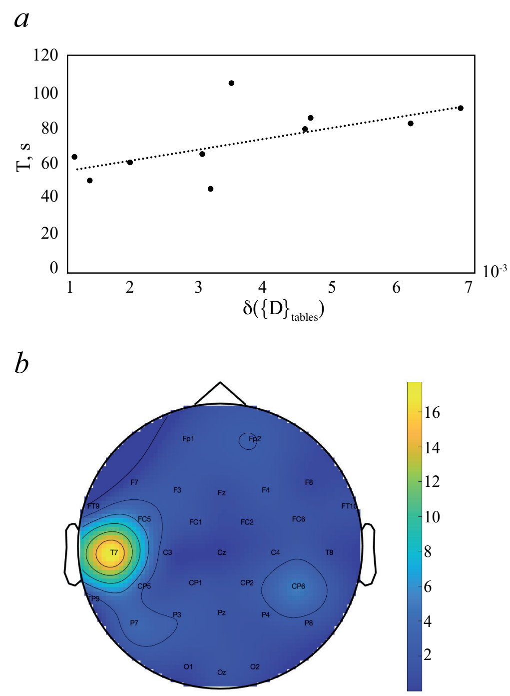

Fig. 3. *a* The dependence of the average execution time of 5 tables on the variance of the distribution of the ratio of the average energies in the beta and alpha ranges for the T7 channel. (*b*) The distribution of F-value on the head surface.

here k is the table number during the solution of which the average energy was calculated.

III. Results

In this work, we analyzed the activity of the brain when performing simple cognitive tasks related to visual attention and perception of symbols. We have found biomarkers of brain activity that can relate the speed of execution of the Schulte table to the electrical activity of the brain. Figure 3 shows the dependence of the average execution time of 5 tables on the variance of the distribution of the ratio of the average energies in the beta and alpha ranges for the T7 channel. This relationship was approximated using linear regression. Statistical testing of the results obtained showed that only the T7 channel is characterized by significant changes (see Figure 3*b*, illustrating the distribution of F-value on the head surface).

IV. Conclusion

Thus, we obtained biomarkers of brain activity in the process of solving cognitive tasks. We used a combination of time-frequency and statistical analysis to calculate activity characteristics. The results obtained can be used to develop neural interfaces for training attention and adjusting the learning process.

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