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A New Electroencephalography Marker of Cognitive Task Performance

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Abstract—A universal biomarker is proposed that is based on calculating the dispersion of the ratio of alpha- and beta-rhythm energies in registered electroencephalography signals and reflecting the level of the components of the cognitive resource of a learner. The Bourdon proofreading test is used as an example to show this biomarker correlates strongly with the main indicators of success in performing standardized cognitive tasks.

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INTRODUCTION

An educational system cannot exist without ways of evaluating performance. Such monitoring allows us to analyze the quality of teaching and make corrections to the education system in a timely manner. Monitoring exists at each stage of teaching in one form or another. A classical approach is to test acquired knowledge and skills, and assess and analyze the mental and personal qualities of learners [1, 2], allowing us to personalize an approach during teaching. Note that the personalization of education has become possible through analyzing the cognitive capabilities of learners. Nevertheless, there are some limits in the conventional approaches in this sphere, one of which is the difficulty of creating individualized ways of testing.

The development of classical approaches to assessing the cognitive characteristics of a person has led to analyzing the activity of the brain using devices for recording electroencephalograms (EEGs). This technology is not costly, and data can be analyzed in real time. An EEG has two main problems that restrict the use of this technology: a long process of preparation (positioning electrodes) and the need to use special conductive gels. However, these barriers are partially overcome by using special caps, dry electrode technologies, and portable electroencephalographs [3]. The range of using systems of a brain–computer interfaces type based on recording EEGs registration has thus grown considerably in daily life [4].

Many works have been dedicated to the studies by using the EEG features of cognitive abilities [5–11]; however, not all of them do not imply using the results obtained from using personalized interfaces. An important problem here is a lack of simple and reliable metrics for assessing the cognitive characteristics of a learner [12]. This work presents a new biomarker for assessing a cognitive load by calculating the standard deviation of the ratio of standard brain rhythms.

METHODOLOGY

We gathered a group of 12 second graders with no health issues. The volunteers and their representatives (parents) acquainted themselves with the experimental procedure and the possible inconveniences it might cause. They also had a chance to ask questions and receive satisfactory answers. The legal representative of each subject completed and signed an informed consent form for participating in the experiment. All experimental work was done in accordance with the Helsinki Declaration of Ethics and approved by Innopolis University's Commission on Ethics. The participants took the Bourdon proofreading test using a form with rows of Cyrillic letters. The form consisted of 20 lines, each of which had a random sequence of 30 letters. The beginning of each row indicated a letter to highlight. A target symbol was encountered in each line from one to six times. The test was performed on an electronic tablet where required letters were highlighted with a stylus. The time spent on an answer and the chosen letter were recorded during the test. The main metric was the average time of answering, which was calculated without regard to the correctness of the answer. This characteristic was therefore an indicator of the average number of symbols looked through per unit of time, which is also one of the quantities assessed in practice [13]. EEGs were registered using an actiCHamp encephalograph with 31 channels of ActiCap electrodes with Ag/AgCl sensors. The electrodes were positioned according to the international

10–10 pattern, with the earthing electrode located on the forehead and one reference electrode in the region of the right mastoid antrum. The frequency of EEG signal sampling while recording was 250 Hz. The signals were filtered from 0.16 to 70 Hz by a bandpass filter and a 50 Hz rejector filter to suppress noise from the mains. Artifacts were eliminated via ICA.

To obtain a time–frequency spectrum, the signals were subjected to a wavelet transform, with the Morlet wavelet being selected as the mother wavelet [14]. The wavelet transform was performed as

$$W(n,s) = \sum_{n'=n-\left\lceil \frac{T(s)}{h} \right\rceil}^{n+\left\lceil \frac{T(s)}{h} \right\rceil} x_{n'} \psi^* \left(\frac{(n'-n)h}{s} \right), \qquad (1)$$

where ψ^* is the Morlet mother wavelet:

$$\psi^*(\eta) = \pi^{-\frac{1}{4}} e^{2\pi i \eta} e^{-\frac{\eta^2}{2}}. \qquad (2)$$

The wavelet transform was performed in the 8–30 Hz frequency band, which corresponded to the ranges of alpha and beta rhythms. Since the mother wavelet was a complex function, we used the transform below for the obtained complex surface, element by element:

$$\frac{1}{s} |W(n,s)|^2 . \qquad (3)$$

We calculated the signal strength on each time scale s, where multiplier $1/s$ was introduced to normalize the wavelet spectrum [14]. To avoid edge effects, we excluded 125 points (0.5 s) from each end of the time series.

Frequency-averaged energies in the alpha (8–15 Hz) and beta (15–30 Hz) ranges were calculated from the time–frequency wavelet spectrum. To estimate the proposed biomarker (the average dispersion of the ratio of rhythms), we analyzed two approaches: (1) separating the time series of energies in selected ranges into windows with a selected length and (2) separating the time series into a certain number of windows. This was done to find the best length of a window. Time averaging was performed in each window. The series of energies obtained in the alpha range was then divided element by element into energies in the beta range, and the standard deviation of the values was calculated for the series of all windows. This number is the characteristic for each participant of the experiment. The resulting values were correlated afterwards into those of the average answering time:

$$r_{xy} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}}, \qquad (4)$$

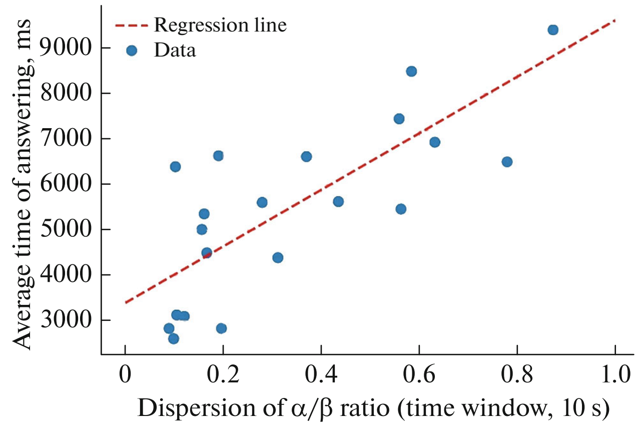

Fig. 1. Dot plot of data on dispersion and the average time of answering at a time window length of 24 s and the linear regression for these data (red line). Index $r = 0.65$, $p = 0.0234$.

where n is the number of participants in the experiment, x_i is the average answering time of the participant denoted as I, $\bar{x}$ is the total average answering time, y_i is the average value of standard deviation of the ratio of energies in alpha- and beta-ranges for the participant denoted as i, and $\underline{y}$ is the total average deviation.

To test the null hypothesis that the data do not correlate, we used the probability density function of index r [15]:

$$f(r) = \frac{(1 - r^2)^{n/2-2}}{B\left(\frac{1}{2}, \frac{n}{2} - 1\right)}, \qquad (5)$$

where B is the β-function. Note that this function is not an accurate representation of the probability density of r. Instead, we use an approximation according to the beta distribution. Testing was done using function (5), the probability distribution function was calculated numerically, and critical values of index r corresponding to significance level 0.05 were computed. The data were considered significant if their index was above or below the calculated threshold value at a positive and negative value of the index, respectively. The data in each EEG channel were tested independently of one another.

RESULTS AND DISCUSSION

A significant correlation was revealed between the dispersion and the average time spent to search for one letter in the correction task (Fig. 1). Analysis of the distribution of the significance level of correlation according to channel showed that a number of channels (the pink regions in Fig. 2) were significant for this type of task, with the minimum p-values being located on the channels of the central parietal region, the frontal pole, and the right temporal lobe. We also

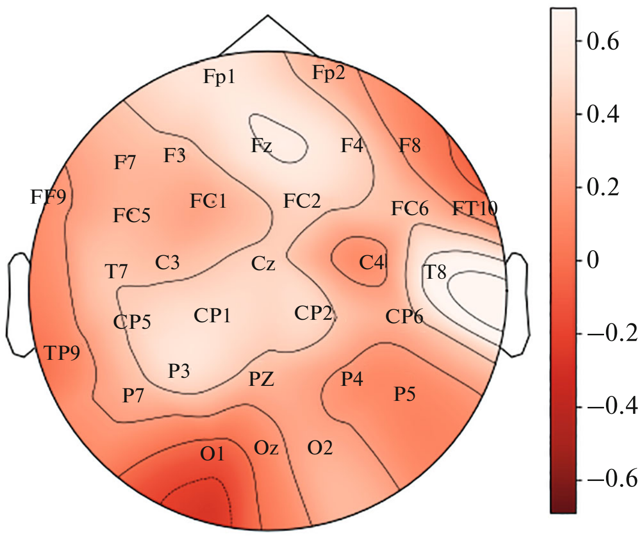

Fig. 2. Topogram of the coefficients of correlation at a time window length of 24 s.

studied the effect the length of the time window, and the number of time windows into which the time of task performance is divided, has on the maximum significance of correlation (Fig. 3). It was found not to depend significantly on the length of the time window (at least when $1 < t_w < 50$ s). To use the system, it is therefore most convenient to set time window length t_w equal to the period of estimating behavioral characteristics in performing the task, since it is then easier to establish a correlation between the quantity of dispersion and task performance.

The effect normalizing EEG signals against the background activity has on the level of correlation was studied as well. It was found that normalizing EEG data against signals of background activity (relative change normalization) makes the correlation insignificant. It is therefore more promising to use the initial EEG data (after they are preliminarily processed to remove artifacts).

Results from analyzing the distributions of significance levels of correlation according to channel allows us to identify the optimum and minimum required configurations of electrodes that provide the most important information about the state of a learner. These include the parietal, central parietal, and frontal electrodes. Our results offer the possibility of substantially reducing the number of electrodes in the brain—computer interface that can be used in the educational process (ranging from 2 to 8, depending on the required accuracy of the system operation). This is critical when implementing the detection algorithm operating in real time, since it considerably lowers the volume of processed data, reduces the cost of neuro headsets, and increases the rate of positioning electrodes.

Since it was found that the proposed characteristic correlates strongly with the main indicators of success in performing standardized cognitive tasks, it can be used as a biomarker of a learner's cognitive state related to teaching and solving assigned tasks. We assume this biomarker reflects the level of components from a learner's cognitive resource (e.g., the level of attention, cognitive fatigue, and working memory load) that determine the efficiency of task performance. This provides new possibilities for developing ways of increasing the efficiency of teaching that are based on normalizing the ratio of brain rhythm energies (and thus dispersion), probably by performing special exercises during breaks between tasks for rhythm correction, or by using biological feedback. Since a proofreading test activates many elementary cognitive functions (e.g., visual search, working memory, and the recognition and processing of letters), our results can be transferred to a wide range of different cognitive tasks.

In developing the experiment, we initially intended to use the percentage of tasks performed correctly by

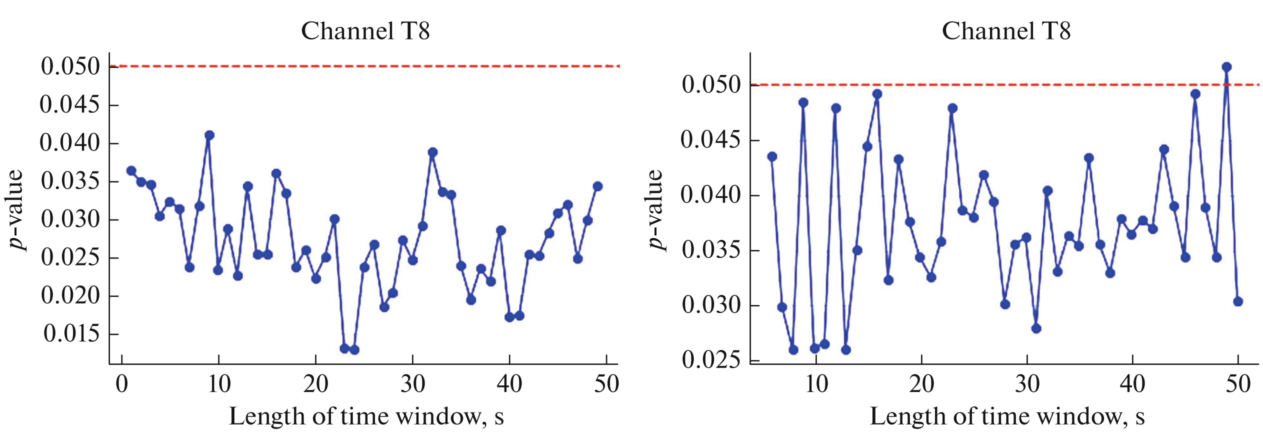

Fig. 3. Significance of the correlation for time windows with fixed lengths (on the left) and fixed numbers (on the right).

each participant as the main behavioral metric. However, this turned out to involve some restrictions resulting from the frequent situation where a test is performed correctly, which increases the bias in the experimental sample toward one where the task is performed 100% correctly. The increase in the test volume also alters the level of fatigue over time, which could negatively affect the results.

Note that the relationship between the rate of test performance and the selected metric could result from the operation of more complex functional networks activating in the brain when performing a task. We plan to consider this issue after finishing research now under way.

CONCLUSIONS

We proposed a universal biomarker that was based on calculating the dispersion of the ratio of alpha- and beta-rhythm energies in registered EEG-signals and reflected the level of components in the cognitive resource of a learner. Using a proofreading test as an example, we showed this biomarker correlates significantly with the main indicators of success in performing standardized cognitive tasks.

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COMPLIANCE WITH ETHICAL STANDARDS

Conflict of interest. The authors declare that they have no conflicts of interest.

Statement of compliance with standards of research involving humans as subjects. All procedures performed in studies involving human participants were in accordance with the standards of the Innopolis University's Commission on Ethics and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants involved in the study.

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