Attention state of children during Schulte tables task

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***Abstract*—We have analyzed EEG signals of children during cognitive load of specific type in order to estimate level of attention during this task. EEG signals were recorded in accordance with proposed design of experiment. For obtained EEG data we have analyzed behavioral characteristics as well as EEG-related characteristics. We have found that behavioural characteristic changes through the task, so may the attention level. We have also found that cognitive task completion is accompanied by appearance of spatial structure — specific distribution of wavelet energy across cortex, which partially changes during completion of the task as well. We believe that changes in attention level are tied to changes in energy distribution, so we suggest this distribution to be used as the marker for attention state estimation.**

***Index Terms*—electroencephalogram, cognitive load, oscillatory patterns, attention, continuous wavelet analysis, frequency ranges**

I. Introduction

The reliable and objective assessment of intelligence and related functions — such as attention — has been a topic of increasing interest of contemporary neuroscience. It is known that intelligence can be measured according to the mental speed of information processing, usually defined through reaction time during elementary cognitive task processing. It is expected that these mental abilities in performing cognitive tasks are associated with the brain's electrical neural activity.

Modern studies on brain activity attract researchers from various fields of science due to interdisciplinary nature of problem. Considerable progress in development of experimental and data processing methods provides instruments for vast and detailed studies of specific phenomena in brain neural network. Recent interdisciplinary works in this field combine approaches of mathematics, physics and nonlinear dynamics with neurophysiological and biological view on the processes in brain neural structures [1]–[11].

The most common method to obtain information about brain activity is electroencephalogram (EEG) [12]. EEG is widely used to study electric activity in different parts of brain in its normal or pathological state. EEG recording procedure suggests placing special electrodes on scalp and recording EEG signals as sum of electric currents generated by group of neurons [13]. EEG signal being a product of complex neuronal network is characterized by complex time-frequency structure with number of specific frequency ranges, oscillatory patterns, noise components (artifacts), etc. [14] It is well-known, that there is a strong connection between EEG time-frequency structure and functional state of organizm [15]. This can be used in studies on specific states, for example, during cognitive task performance [16]–[20].

One of the common ways to estimate subjects intelligence is to measure the mental speed, i.e. the speed of information processing [21]. For this purpose, elementary cognitive tasks (ECTs) are used and the reaction time to perform them is studied. One of the most popular types of ECT is so-called paper-and-pencil test due to simplicity of its implementation and subsequent data analysis [22]. Elementary ECTs are based on the Hick paradigm [23]: there is a linear correlation between the amount of processed information and the reaction time of the subject. The reaction time in its turn can be estimated with Sternberg memory scanning task [24], according to which the reaction time increases linearly with the memory set size. Thus, there is a direct correlation between mental speed and mental abilities (intelligence), i.e., more intelligent individuals exhibit lower reaction time and therefore higher speed of information processing.

Combination of ECTs and simultaneous EEG recording is a

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promising approach. Studies suggest, that there are particular EEG features correlated with intelligence, attention and other brain characteristics [4], [9], [25]. EEG-based method for estimation of subjects intelligence and attention level would find social application, for instance, in education.

In this work we analyzed EEG signals of children recorded during specific cognitive task — Schulte test. We analyzed behavioural characteristics – time intervals required for subject to find each consequtive number in Schulte table as well as EEG-related characteristics — wavelet energies averaged over alpha and beta frequency ranges. We also performed statistical analysis of these characteristics with help of ANOVA to find features that can be used to evaluate level of attention and its dynamics during task completion.

II. Methods

Ten healthy children (7-10 years), right-handed, with normal or corrected-to-normal visual acuity participated at the experiment. All of them were asked to maintain a healthy life regime with an 8-hrs night rest during 48 hrs prior the experiment. Parents of each volunteer provided informed written consent before participating in the experiment. The experimental procedure was performed in accordance with the Helsinki's Declaration.

For EEG recording we used electroencephalograph"actiCHamp" by Brain Products (Germany). EEG was recorded for 31 channels according to "10-10" system with ground electrode placed in the "Fpz" position on the forehead and one reference electrode on the right mastoid. For EEG signal recording we used "ActiCap" — active Ag/AgCl electrodes (one for each EEG channel) placed on the scalp with the help of special cap. To increase the skin conductivity we treated scalp skin with abrasive "NuPrep" gel before the experiment and placed EEG electrodes on conductive "SuperVisc" gel. After the electrodes were placed, we monitored the impedance to get best possible quality of EEG recordings. Common impedance values were < 25 kΩ which is quite sufficient for active EEG electrodes. EEG signals were recorded with sampling rate of 1000 Hz and filtered by band-pass filter (cutoff frequencies at 0.016 Hz and 70 Hz), as well as 50-Hz notch filter.

Experiment was performed using tablet computer with pencil. Experimental design suggested that the subject performed specific cognitive task and EEG signals were recorded during this process. Cognitive task was to accomplish Schulte test — simplified version of Zahlen-Verbindungs-Test (ZVT), widely used in Russia. Schulte test consisted of matrices (tables) of $5 * 5$ randomly arranged numbers from 1 to 25. The subject was asked to find numbers in a descending order from 25 to 1 by pointing each found number with a pencil. We registered time intervals Δt_m between picking subsequent numbers ($m = 1, 2...25$). All participants completed R = 5 tables (50-90 s for each table) under direct supervision of a professional psychologist. Between tables the subject had a short break for 10-20 s.

For detailed time-frequency analysis of EEG signals continuous wavelet transform (CWT) was used [5], [26]. During recent interdisciplinary studies this method recommended itself as a powerful instrument for analysis of experimental biological data and obtaining essential information about complex dynamics of physiological systems including brain [27], [28].

The CWT is computed as convolution of EEG signal $x(t)$ with wavelet basis $\varphi_{s,\tau}$:

$$W_n(s,\tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x_n(t) \varphi^*_{s,\tau}(t) dt, \tag{1}$$

where n = 1, 2... N is the number of EEG channel (N = 31) and "*" stands for complex conjugation. Each function $\varphi_{s,\tau}$ from the basis can be obtained from one function φ_0 called mother wavelet:

$$\varphi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \varphi_0 \left(\frac{t - t_0}{s} \right), \tag{2}$$

where s — time scale responsible for extension/compression of mother wavelet, t_0 — time shift of mother wavelet. In the present study complex Morlet mother wavelet was used since it has recommended itself in studies on neurophysiological data:

$$\varphi_0(\eta) = \pi^{-\frac{1}{4}} e^{j\omega_0 \eta} e^{-\frac{\eta^2}{2}}, \tag{3}$$

where parameter $\omega_0 = 2\pi$ is the central frequency of Morlet wavelet, $\eta = \frac{t - t_0}{s}$.

One of the common ways to interpret CWT results is to consider wavelet energy:

$$E(f,\tau) = |W(f,\tau)|^2 \tag{4}$$

Surface of CWT energy (wavelet spectrum) provides information about time-frequency structure of the signal, such as length of some pronounced oscillatory patterns and their main frequencies.

Wavelet energy spectrum is commonly analyzed in number of specific frequency bands: delta, theta, alpha, beta . Energy in beta (15-30 Hz) and alpha (8-13 Hz) bands is especially important since it is often used to characterize cognitive processes including attention and its stability. For these two particular frequency bands averaged wavelet energy was calculated as:

$$E_{\alpha,\beta}(t) = \frac{1}{\Delta f_{\alpha,\beta}} \int_{f \in f_{\alpha,\beta}} E(f,t) df, \tag{5}$$

where $\Delta f_{\alpha,\beta}$ — width of alpha and beta frequency ranges correspondingly.

The wavelet analysis of EEG recordings was performed with developed C/Cuda software for increasing computation performance [29].

For statistical analysis we used ANOVA (ANalysis Of VAriance), which is widely used to analyze the differences among group means in a sample.

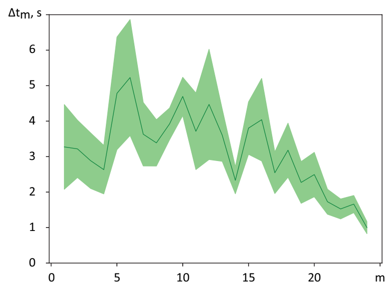

Fig. 1. Dependence of time interval's length Δt_m (mean and standard error) on sequence number m.

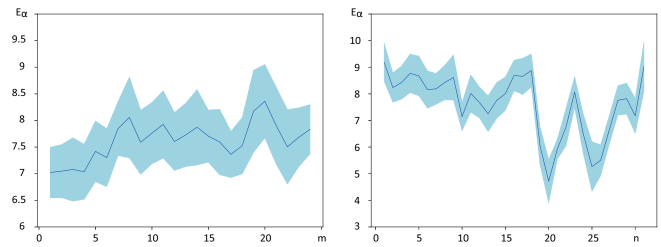

Fig. 2. Dependence of E_α (mean and standard error) on sequence number m (a) and channel number n (b).

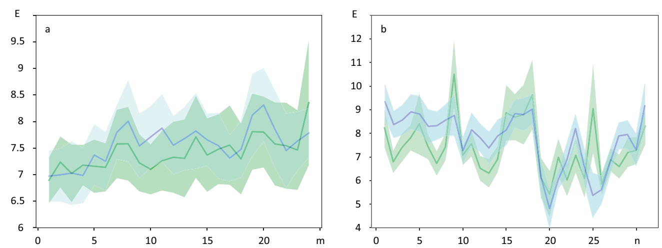

Fig. 3. Dependence of E_β (mean and standard error) on sequence number m (a) and channel number n (b).

III. Results

In the first part of our work we compared distributions of time intervals Δt_m in two subsequent Schulte tables. We had chosen table number (two tables overall) and sequence number $m = 2, 3...25$ as two factors for ANOVA. While there are 25 overall numbers with 25 corresponding time intervals in each table, we rejected Δt_1 and considered only 24 time intervals. This was done because Δt_1 was determined not only by searching process of number "25" but also by initial preparation for the task, thus Δt_1 varied greatly in the group of subjects.

Statistical analysis showed that average length of time intervals Δt_m has no significant variation between the first and the second Schulte tables ($F(1, 6) = 5.76, p = 0.053$). However, the length of specific time interval Δt_m significantly depends on sequence number m ($F(23, 138) = 2.085, p = 0.005$). These results are shown on Fig. 1.

At the same time, dependence of Δt_m on two joint factors (table number and sequence number m) is not significant ($F(23, 138) = 0,636, p = 0.897$). These results lead to safe assumption that time interval required to find the next number in sequence depends significantly only on sequence number m and not on table number.

In the second part we analyzed distributions of characteristics $E_{\alpha,\beta}$, averaged over each time interval Δt_m. In this case we had chosen sequence number $m = 2, 3...25$ and channel number $n = 1, 2...31$ as two factors for ANOVA.

We found that for E_α there is a significant dependence on sequence number m ($F(23, 128) = 1.840, p = 0.017$) (see Fig. 2a) and on channel number n ($F(30, 180) = 7.6, p < 0.001$) (see Fig. 2b), however, joint influence of these two factors is not significant ($F(690, 4140) = 0.5, p = 0.851$). These results can imply that some characteristic spatial distribution of wavelet energy E_α is formed in cortex during the search of each number in Schulte table. The form of this distribution is not dependent on sequence number m and yet the mean value of E_α changes from number to number.

For E_β analysis showed that dependence on sequence number m is not significant ($F(23, 128) = 1.4, p = 0.117$) (see Fig. 3a) and dependence on channel number n is significant ($F(30, 180) = 3.5, p < 0.001$) (see Fig. 3b). At the same time, joint influence of m and n factors is not significant ($F(690, 4140) = 1.05, p = 0.175$). These results suggest that as in case of E_α characteristic spatial distribution of wavelet energy E_β is formed in cortex during the search of each number in Schulte table, however, the form of this distribution and the mean value of E_β are not dependent on sequence number m.

Fig. 2b and Fig. 3b can be used to analyze overall spatial distribution of wavelet energy in cortex and to estimate areas of activity. Fig. 2b shows that there is a well-pronounced drop in level of wavelet energy E_α for channels $n = 19, 20, 21$ and $n = 24, 25, 26$. According to "10-10" system these numbers correspond to channels in occipital and temporal areas. On the other hand, distribution of E_β on Fig. 3b demonstrates significant maxima for channels $n = 9$, $n = 15, 16, 17, 18$ and $n = 25$ related to occipital and temporal areas as well. While high beta-rhythm and low alpha-rhythm activity in occipital area can be explained by heavy load on visual cortex caused by Schulte test, activity in temporal areas seems to be more attractive for studying. For instance, it is known [30], [31] that during visual non-verbal tasks in children alpha-rhythm activity decreases and beta-rhythm activity simultaneously increases in temporal areas.

Significant increase in high-frequency activity is observed when mental activity includes elements of novelty, while stereotypic, repeated mental operations are accompanied by decrease of activity in beta frequency range. Increased beta activity in the temporal areas probably appears due to the fact that non-verbal stimuli in our case (Schulte test) are unusual for children and include an element of novelty [32].

IV. Conclusion

In this paper we analyzed EEG signals of children recorded during specific cognitive task – Schulte test. We analyzed behavioural characteristics – time intervals required for subject to find each consequtive number in table (Δt_m) as well as EEG-related characteristics calculated with help of CWT — wavelet energies averaged over alpha and beta frequency ranges ($E_{\alpha,\beta}$). We performed statistical analysis of these characteristics with help of ANOVA. We have found that behaviour characteristic Δt_m changes through the task, which leads to assumption that some performance charateristics (such as attention) can change during completion of the task as well. We have also found that cognitive task completion is accompanied by appearance of spatial structure — specific distribution of E_α and E_β energies across cortex. Results of statistical analysis showed that this spatial structure partially changes during completion of the task. We believe that changes in attention level are connected to changes in energy distribution and, as the result, to changes in brain activity signals. We suggest this distribution to be used as the marker for attention state estimation.

Knowledge on attention state estimation can be helpful for further fundamental studies on cognitive load and attention state. Obtained results can also be applied, for example, in development of teaching assistant system for children.

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