Features of brain activity in children during cognitive tasks of different types

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***Abstract* — EEG signals of children were recorded during cognitive load of various types in accordance with proposed design of experiment. Obtained EEG data were analyzed with methods of time-frequency analysis and statistics. Differences in time-frequency structure of EEG signals and ratio between frequency ranges was shown for background activity and two types of cognitive activity.**

Keywords* — *cognitive task, children, electroencephalogram, continuous wavelet transform, frequency ranges, attention state

I. INTRODUCTION

One of the common ways to estimate subject's intelligence is to measure the mental speed, i.e. the speed of information processing [1]. For this purpose, elementary cognitive tasks (ECTs) are used and the reaction time to perform them is studied [2, 3]. 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 [2]. Elementary ECTs are based on the Hick paradigm [4]: 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 [5], according to which the reaction time increases linearly with the memory set size. A similar idea underlies the letter matching paradigm [6] which associates reaction time with the speed of lexical access. 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 [7].

Another very promising approach to firmly extract cognitive components is the use of information about electrical brain activity. This information can be obtained using number of experimental techniques, for example, electroencephalogram (EEG) [8]. Studies suggest, that there are particular EEG features correlated with intelligence, attention and other brain characteristics [9-12]. EEG-based method for estimation of subject's intelligence and attention level would find social application, for instance, in education.

II. MATERIALS AND METHODS

A. Experiments

Seven 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 "10-20" system. Experiment was performed using tablet computer and design included several phases in the following order: background activity, cognitive task 2, cognitive task 1, cognitive task 2. Background activity was recorded at the start of experimental session for 90 s. During this phase subject sat still with opened eyes and without performing any task. Cognitive task 1 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. by pointing each found number with a pencil. All participants had to complete R = 5 tables (50-90 s for each table) under direct supervision of a professional psychologist. Between tables subject had a break for 10-20 s. Cognitive task 2 consisted of watching a video – short cartoon with content appropriate for children. Duration of each video was ~300 s.

B. Data analysis

We analyzed time-frequency representations of EEG signals obtained via a continuous wavelet transform (CWT), which has recently become a very popular technique for studying dynamics of neurophysiological brain activity [13-17]. CWT is a convolution of EEG signal $x(t)$ with basic function $\psi(\eta)$ as

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

where $n = 1, 2 \dots N$ is the number of EEG channel ($N = 31$) and '*' stands for complex conjugation. As mother wavelet of CWT we used the complex Morlet wavelet

$$\psi(\eta) = \frac{1}{\sqrt[4]{\pi}} e^{j\omega_0\eta} e^{-\eta^2/2} \qquad (2)$$

where $\eta = f(t - t_0)$ and $\omega_0 = 2\pi$ is the wavelet central frequency.

We analyzed wavelet energy spectrum as $E^n(f,t) = \sqrt{W_n^2(f,t)}$ in number of frequency bands: delta (2-4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (15-30 Hz). For these particular frequency bands averaged wavelet energy was calculated as:

$$E^n_{\delta,\theta,\alpha,\beta}(t) = \frac{1}{\Delta f}\int_{f\in f_{\delta,\theta,\alpha,\beta}} E^n(f,t)df \qquad (3)$$

The ratio between EEG signal energies in beta and alpha frequency bands, especially in occipital area, is often used to characterize attention and its stability. However, in some instances the ratio of EEG energy for high frequencies (HF) and low frequencies (LF) provides more evident results. For example, Liutsyuk et al. [12] found that the subjects with good working ability displayed relatively high values of HF/LF ratio. Moreover, this ratio was greater in the right hemisphere, that probably indicated stronger contribution of neuronal activity in this hemisphere to provide stability of attention.

Thus, we were interested in analysis and comparison of following frequency ranges: alpha and beta, LF ($E^n_{LF}(t) = E^n_\delta(t) + E^n_\theta(t) + E^n_\alpha(t)$) and HF ($E^n_{HF}(t) = E^n_\beta(t)$). The ratio between HF and LF was calculated for each EEG channel as following:

$$\varepsilon^n(t) = \frac{E^n_{HF}(t)}{E^n_{LF}(t)} \qquad (4)$$

Then coefficients $\varepsilon^n(t)$ were averaged separately for channels in left and right hemisphere (13 channels for each hemisphere according to "10-20" system) to obtain $\varepsilon^L(t)$ and $\varepsilon^R(t)$ correspondingly. Wavelet energies for alpha and beta rhythm were averaged for EEG channels in occipital area (6 channels) to obtain $E^O_\alpha(t)$ and $E^O_\beta(t)$ correspondingly.

The wavelet analysis of EEG recordings was performed withg home written C/Cuda software for increasing computation performance [14].

III. Results

We analyzed EEG signals for each epoch in experiment separately: background activity, Schulte tables – each table as individual epoch, video watching – two separate epochs, one for each video. Corresponding EEG fragments were processed with CWT and following characteristics were calculated: $\varepsilon^L(t)$, $\varepsilon^R(t)$, $E^O_\alpha(t)$, $E^O_\beta(t)$. Examples of acquired distributions are illustrated on Fig. 1-3.

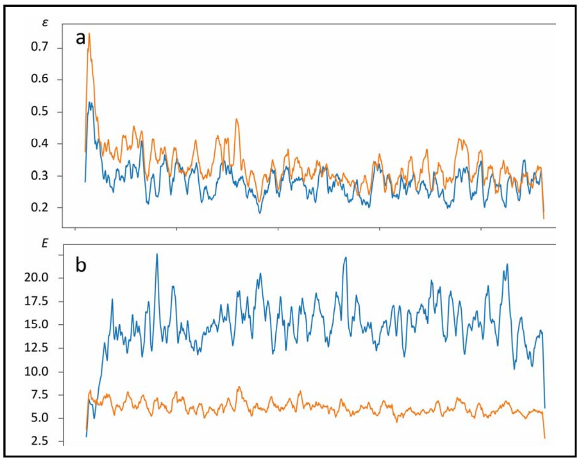

Fig. 1. Results for background epoch: (a) distributions of $\varepsilon^L(t)$and $\varepsilon^R(t)$ (blue and orange colors correspindingly); (b) distributions of $E^O_\alpha(t)$and $E^O_\beta(t)$ (blue and orange colors correspindingly)

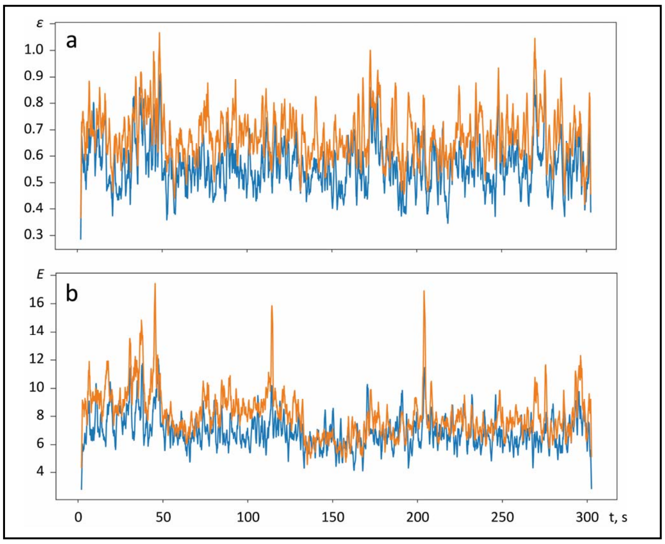

Fig. 2. Results for video watching epoch: (a) distributions of $\varepsilon^L(t)$and $\varepsilon^R(t)$ (blue and orange colors correspindingly); (b) distributions of $E^O_\alpha(t)$and $E^O_\beta(t)$ (blue and orange colors correspindingly)

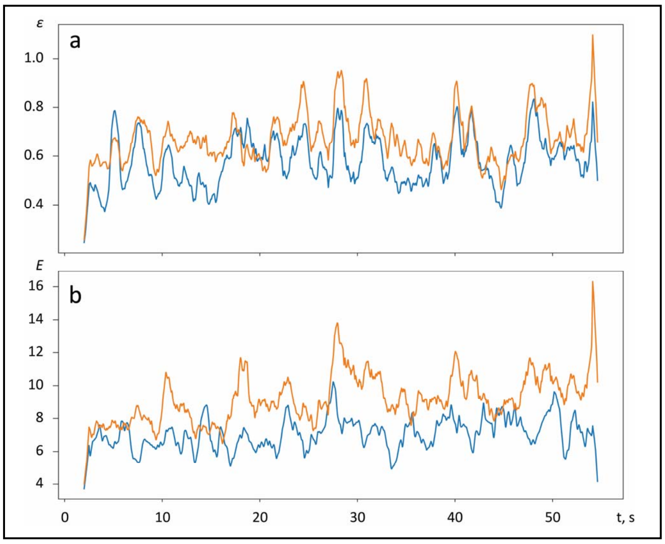

Fig. 3. Results for Schulte table epoch: (a) distributions of $\varepsilon^L(t)$and $\varepsilon^R(t)$ (blue and orange colors correspindingly); (b) distributions of $E^O_\alpha(t)$and $E^O_\beta(t)$ (blue and orange colors correspindingly)

By comparing Fig. 1 with Fig. 2 or Fig. 3 one can see, that see that during background epoch alpha rhythm is dominating (see Fig. 1b), which also leads to lower values of $\varepsilon^L(t)$ and $\varepsilon^R(t)$ (see Fig. 1a). These features can be used for simple separation of background epochs from ones with cognitive tasks.

However, this method ca not be used to distinguish Schulte table epoch from epoch with video: values of $\varepsilon^L(t)$, $\varepsilon^R(t)$, $E^O_\alpha(t)$, $E^O_\beta(t)$ on Fig. 2 are very close to corresponding ones on Fig. 3.

For better comparison of energy in different frequency ranges we calculated difference between HF/LF ratio in right and left hemisphere as $\varepsilon^{R-L}(t) = \varepsilon^R(t) - \varepsilon^L(t)$ and difference between beta and alpha rhythm in occipital area as $E^O_{\beta-\alpha}(t) = E^O_\beta(t) - E^O_\alpha(t)$. Then these characteristics were time-averaged for each epoch separately ($\langle\varepsilon^{R-L}\rangle$ and $\langle E^O_{\beta-\alpha}\rangle$).

We found, that $\langle \varepsilon^{R-L} \rangle = 0.09 \div 0.1$ for Shulte tables while for epoch with video $\langle \varepsilon^{R-L} \rangle \sim 0.11$. In terms of $\langle E^{O}_{\beta-\alpha} \rangle$ difference between Schulte table and watching of video is more pronounced: $1.5 \div 2.1$ and $0.6 \div 1.1$ correspondingly.

Revealed differences between background activity and cognitive tasks of different types can be used in further research on fundamental properties of brain related to cognitive activity in children, especially during educational process. It also can be used in development of EEG-based method for evaluation of intelligence and attention level.

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