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Brain-computer interface for alertness estimation and improving

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ABSTRACT

Using wavelet analysis of the signals of electrical brain activity (EEG), we study the processes of neural activity, associated with perception of visual stimuli. We demonstrate that the brain can process visual stimuli in two scenarios: (i) perception is characterized by destruction of the alpha-waves and increase in the high-frequency (beta) activity, (ii) the beta-rhythm is not well pronounced, while the alpha-wave energy remains unchanged. The special experiments show that the motivation factor initiates the first scenario, explained by the increasing alertness. Based on the obtained results we build the brain-computer interface and demonstrate how the degree of the alertness can be estimated and controlled in real experiment.

Keywords: Electroencephalogram, continuous wavelet analysis, brain-computer interface, alertness

1. INTRODUCTION

Estimation of the characteristic features of the human's psychophysical state based on the signals of electrical brain activity (EEG) is an exciting topic of neuroscience. In this case, the most studied characteristics of a person's psychophysical state are the concentration of attention and degree of alertness.[1,2] Estimation of these individual factors was actively studied in[3] in the context of the implementation of interfaces for monitoring the psychophysical state of operators with heavy workload. Recently, the analysis of the processes associated with the switching of attention, is used to develop neurointerfaces for completely paralyzed people,[4] and the development of systems for training attention, in particular for children with attention deficit hyperactivity disorder.[5]

Although the significant progress has been made in the field of estimating human alertness from the multichannel signals of brain electrical activity, the task of developing techniques that allow to estimate and control changes in the degree of alertness in real time is still poorly understood.[6]

At the same time, latter is important for the development of brain-computer interfaces (BCIs) that allow to evaluate and monitor a person's psychophysical state.[5]

In the framework of the current research problem we have studied the EEG signatures, associated with the degree of human alertness. We have recorded and analyzed multichannel EEG recordings from the human being subjected to the experimental task, which consists in consecutive interpretations of a large number of visual ambiguous stimuli. Having considered changes in the energy of different oscillatory modes of EEG signals, we have found that ratio between the energy of α- and β-rhythms can be used for the quantitative assessment of the degree of human alertness. Based on the obtained result we have developed the brain-computer interface and demonstrated how the degree of the alertness can be estimated and controlled in real experiment.

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2. METHODS

Twenty healthy subjects males and females, between the ages of 20 and 43 with normal or corrected-to-normal visual acuity participated in the experiments. All of them provided informed written consent before participating in the experiment. The experimental studies were performed in accordance with the Declaration of Helsinki and approved by the local research ethics committee of the Yuri Gagarin State Technical University of Saratov.

The Necker cube[7,8] was used as the visual stimuli, Such ambiguous stimulus is a popular object of many psychological experiments[9–11] and theoretical models.[11–13] It represents itself a cube with transparent faces and visible ribs; an observer without any perception abnormalities sees the Necker cube as a 3D-object due to the specific position of the cube's ribs. Bistability in perception consists in the interpretation of this 3D-object as to be either left- or right-oriented depending on the contrast of different inner ribs of the cube. The contrast $I \in [0, 1]$ of the three middle lines centered in the left middle corner was used as a control parameter like that which was considered in Ref.[14] The values $I = 1$ and $I = 0$ correspond, respectively, to 0 (black) and 255 (white) pixels' luminance of the middle lines. Therefore, we can define a contrast parameter as $I = y/255$, where y is the brightness level of the middle lines using the 8-bit grayscale palette.

All participants were instructed to press either the left or right key depending on their first impression of the cube orientation at each presentation. The whole experiment lasted around 10–15 min for each participant, including short recordings of the brain background activity before and after the stimuli presentation. During experimental sessions, the cubes with different I were randomly presented (each configuration for about 30 times) and the electrical brain activity was recorded using the electroencephalographic recorder Encephalan-EEGR-19/26 (Medicom MTD, Russia) which provided simultaneous registration of up to 20 EEG channels and a two-button input device. The monopolar registration method and the classical ten-twenty electrode system were used. The ground electrode N was located above the forehead and two reference electrodes $A_{1,2}$ were located on mastoids. The EEG signals were filtered by a band pass filter with cut-off points at 1 Hz (HP) and 100 Hz (LP) and a 50-Hz Notch filter. The electroencephalograph "Encephalan–EEGR–19/26" (Taganrog, Russian Federation) with multiple EEG channels was used for amplification and analog-to-digital conversion of the EEG signals.

The gray-scale images were demonstrated on the 24" BenQ LCD monitor with a resolution of 1920×1080 pixels and a refresh rate of 60 Hz. The subject was located at a distance of 70–80 cm from the monitor with a visual angle of approximately 0.25 rad.

3. ANALYSIS AND RESULTS

For the experimental procedure all subjects were divided into two equal groups, 10 financially motivated and 10 non-motivated. The members of the motivated group had a concrete task: try to identify all the cubes as correctly as possible. The members of the second group were unpaid volunteering students and staff, who participated in experimental sessions daily at random hours. Participants of both groups were subjected to 40-min sessions during which 400 Necker cube images were presented.

The whole experimental series were split into number N_{tr} 3-sec trials associated with perception of each individual stimulus. Each trial consisted of three subsequent segments: (I) before image presentation, (II) during presentation, and (III) after presentation.

We analyzed the EEG signals recorded by five electrodes (O_1, O_2, P_3, P_4, P_z) placed on the standard positions of the ten-twenty international system,[15] using the continuous wavelet transform.[16] The 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 $f \in [1, 30]$ Hz. Here $W_n(f,t)$ is the complex-valued wavelet coefficients calculated as

$$W_n(f,t) = \sqrt{f} \int_{t-4/f}^{t+4/f} X_n(t)\psi^*(f,t)dt, \tag{1}$$

where $n = 1, ..., N$ is the EEG channel number ($N = 5$ being the total number of channels used for the analysis in this paper) 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

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

where $\omega_0 = 2\pi$ is the central frequency of the Morlet mother wavelet.[17] Wavelet energy spectrum $E(f,t)$ was calculated for each trial by averaging corresponded values of $E^n(f,t)$ over the set of occipital EEG channels. Obtained values $E(f,t)$ were then averaged over N_{tr} trials. The resulted time-frequency plots are shown in Fig. 1 *a,b* for subjects from first and second group, respectively. Depending on the obtained dependencies $E(f,t)$ two different scenarios were identified. The first scenario was characterized by a significant decrease in the energy of α-rhythm during the segment II (perception) with a simultaneous relatively high increase in the energy of β-activity. The second scenario was distinguished by a strong contribution of α-rhythm and much lower pronounced generation of β-rhythm during all segments.

In order to quantify spectral features of the scenarios The wavelet energy was calculated for all segments for three frequency bands: $\Delta f_\delta = [1-4]$ Hz (δ-rhythm), $\Delta f_\alpha = [8-12]$ Hz (α-rhythm), and $\Delta f_\beta = [20-30]$ Hz (β-rhythm), corresponding to typical patterns of the human cognitive activity.

Obtained values were averaged over the set of EEG channels, trials and participants within first and the second group. Results are shown in Fig. 1 *c,d* for the first and second group, respectively. Error bars illustrate standard deviation. One can see that people in the first group demonstrate the significant decrease in α-activity and increase in β-activity, associated with the perception of the stimuli. It means that the motivation factor causes the prevalence of the first scenario. One can suppose that increase in motivation makes subject to percept stimuli more carefully. This also causes the increase in the degree of human alertness. Moreover, the obtained quantitative features of the first scenario (which is associated with the high degree of alertness) allow to estimate the degree of human alertness in real time. Latter can be implemented via the brain-computer interface, based on the analysis of electrical brain activity in on-line mode.

In the framework of our research we built a brain-computer interface based on the EEG recorder Encephalan-EEGR-19/26 (Medicom MTD, Russia) supplemented by a special home-made developed acquisition software. A special library from Medicom MTD allowed us to access the data in real time with a sample rate of 250 Hz. The set of $N = 5$ EEG channels (P_3, O_1, P_z, P_4, O_2) arranged according to "10-20" scheme were used for real-time data processing. The wavelet spectrum of the EEG signals was calculated using a floating window of 2-sec length in the range between 4 Hz and 30 Hz.[18] Each event, associated with the presentation of single visual stimulus was analyzed separately in alpha and beta frequency bands on a 1-sec interval preceding the presentation and followed by the moment of the stimulus appearance. A special digital trigger sent by the software together with the presentation of the stimuli initiated the calculation. As a result, the set of values A_I, A_{II}, B_I, B_{II} were calculated for each presentation as

$$A_{I,II} = \sum_{n=1}^{N}\int_{t\in\Delta t_{I,II}} \xi^n(t')dt', \text{ where } \quad \xi^n(t) = \begin{cases} 1, & \text{if} \quad f^n_{max} \in \Delta f_\alpha, \\ 0, & \text{if} \quad f^n_{max} \notin \Delta f_\alpha. \end{cases} \tag{3}$$

$$B_{I,II} = \sum_{n=1}^{N}\int_{t\in\Delta t_{I,II}} \xi^n(t')dt', \text{ where } \quad \xi^n(t) = \begin{cases} 1, & \text{if} \quad f^n_{max} \in \Delta f_\beta, \\ 0, & \text{if} \quad f^n_{max} \notin \Delta f_\beta. \end{cases} \tag{4}$$

where $N = 5$ is the number of EEG channels and f^n_{max} is the location of the maximal spectral component.

The obtained values were averaged over six presentations and the control characteristic $G(t)$ was calculated as

$$G(t) = \frac{(< A_I > - < A_{II} >) + (< B_{II} > - < B_I >)}{2}, \tag{5}$$

where $< ... >$ means the average over six presentations.

The value of $G(t)$ was calculated using Eqs. (3-5) in real time. This value reflected the intensity of the brain response on the appearing visual stimuli. According to the results, describe above, large values of $G(t)$ were

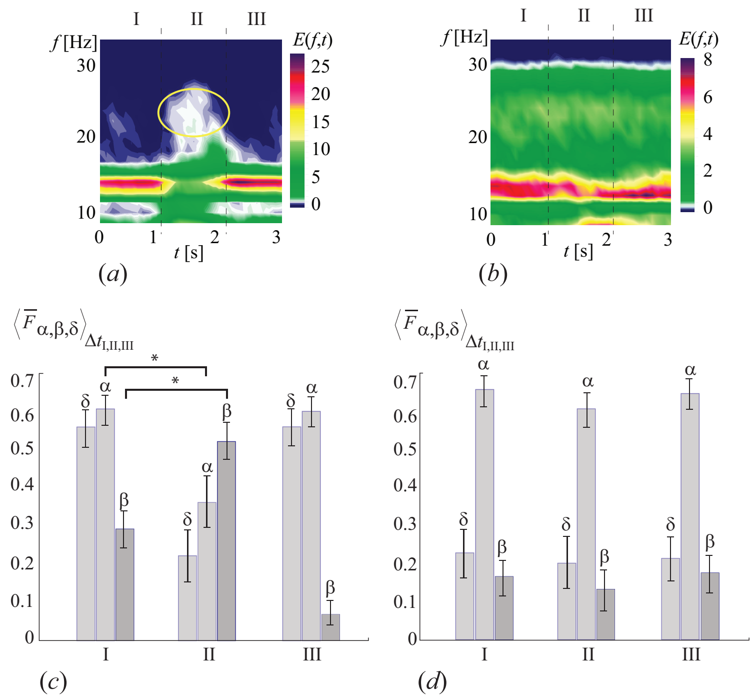

Figure 1. The value of wavelet energy, averaged over the trials and EEG channels for the subject of the first (a) and the second (b) group. The values of the wavelet energy, calculated for each segment (I, II, III) in different frequency bands (α, β, δ) and averaged over the subjects of the first (c) and the second (d) group.

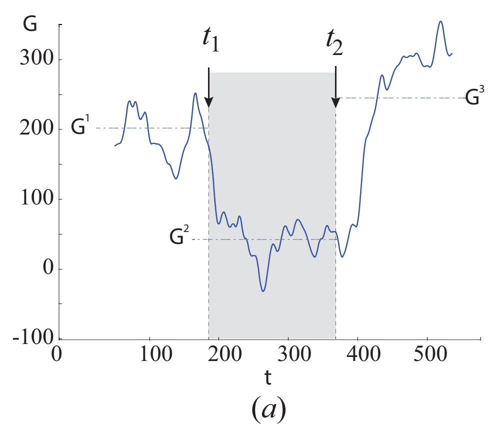

Figure 2. Typical dependency of the control characteristic $G(t)$, reflected the degree of human alertness, on the time, calculated for one subject, shaded region corresponds to time interval for which the subject is affected by external influence

associated with the case when the significant decrease in α-activity and significant increase in β-activity took place. It was connected with the careful procession of the images by the subject (high degree of the subject's alertness). Small values of $G(t)$ were vise-versa associated with the case, when subject did not pay so much attention to visual stimuli (low degree of the subject's alertness).

The developed BCI was experimentally tested on three volunteers. In this experiment, each subject participated in three 4-min subsequent sessions. The experimental results are illustrated in Fig. 2 (a, b). The left and right arrows indicate, respectively, the moments of time, t_1 and t_2, when the external influence was switched on and switched off, respectively. These moments divided the experiment into three sections. During the first section ($t < t_1$), the subject performed the task in the absence of external influence. One could see that $G(t)$ fluctuated near a certain mean value of G^1, individual for each subject. The second section ($t_1 < t < t_2$) included the external influence on the subject in the form of an additional cognitive task. It was easy to see that when the external influence took place, the value of $G(t)$ sharply decreased and oscillated near the mean value G^2, significantly lower than the mean in the first section. Finally, the third section started at ($t = t_2$) demonstrated the effect of restoring attention on the visual stimuli. One could see that $G(t)$ significantly increased for all subjects and oscillated near the mean values $G^3_{1,2,3}$.

It is important to note that a significant change in $G(t)$ is observed within a relatively short time interval (less than 30 seconds) during which the visual stimulus is presented about 5 times. This means that the significant change in the degree of human alertness can be promptly detected and controlled in real time.

4. CONCLUSION

Alertness is known as the state of active attention, characterized by high sensory awareness. This feature of the human's psychophysical state is very important to be estimated in real time.

In the current paper we have analyzed the time-frequency structure of EEG signals, associated with the perception of ambiguous visual stimuli in two groups of participants - financially motivated paid participants and non-motivated volunteers and shown that the additional motivation which increases human alertness, causes the stimulus-related modulation of the energy of α- and β-activity. Based on the obtained results we have introduced the method which allows to estimate the efficiency of such energy modulation in real time.

This method has been implemented in brain-computer interface for the estimation the degree of alertness in real time. Application of the BCI for the monitoring of the degree of alertness in the condition of external stimuli demonstrates that the decrease of the degree of alertness caused by the distraction can be detected.

It should be noted that the revealed phenomena can be associated not only with visual perception of bistable object, but also with other types of cognitive tasks which require a high level of alertness. The demonstrated possibility of the assessment of the brain response to the visual task by a real-time processing of the EEG signals, have possible important applications in monitoring and controlling human attention and alertness during tasks which require substantial attention, e.g., air traffic control, monitoring nuclear power plants, development of training programs and tests of human psychological conditions. This also opens the possibility to estimate the variation of the degree of human attention in time, which is necessary for the development of systems for control and training.

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