Development of the approach to collaborative BCI

Vadim Grubov
Neuroscience and Cognitive Technology Lab, Center for Technologies in Robotics and Mechatronics Components
Innopolis University
Innopolis, Russia
v.grubov@innopolis.ru

Vladimir Maksimenko
Neuroscience and Cognitive Technology Lab, Center for Technologies in Robotics and Mechatronics Components
Innopolis University
Innopolis, Russia
v.maksimenko@innopolis.ru

Vladimir Nedaivozov
Neuroscience and Cognitive Technology Lab, Center for Technologies in Robotics and Mechatronics Components
Innopolis University
Innopolis, Russia
fdf_het@mail.ru

***Abstract*—In the present study we aim to find specific characteristic based on brain activity, that can be used to evaluate attention and, thus, can be used in brain-computer interface. We propose an approach to collaborative BCI aimed to enhance human-to-human interaction while performing shared visual task. We also describe the setup for such BCI and its possible application in long task of classifying ambiguous visual stimuli with varying degrees of ambiguity by a group of people.**

***Index Terms*—brain-brain interface, workload distribution, visual task, visual attention**

I. Introduction

The brain-computer interface (BCI) development is one of the novel multidisciplinary tasks in neuroscience, physics and engineering. The BCI transforms characteristic features of operator's brain activity into computer commands for controlling software and/or hardware in real-time. Such modern technology can find applications in various applied fields, including medicine, industry, robotics, etc. [1]–[5] For example, BCIs can be used for rehabilitation of patients with physical and mental injuries as well as for enhancing cognitive abilities of healthy subjects [6]–[16].

The latter concept led to proposal of the brain-to-brain interfaces (BBIs), that enable direct information transfer between the brains of interacting humans and/or animals. The BBI can be used to enhance the performance of two operators during the shared cognitive task with high mental load by adding interaction between operators. The natural evolution in this direction is the concept of collaborative BCIs [17], [18], which aimed to use multi-brain computing to further enhance human performance.

Such collaborative BCI can be useful for improving the cognitive performance in the group of people subjected to a shared work task that requires sustained attention and alertness. For example, pilots of military or civil aircraft [19] or operators of power plants [20], whose work is associated with a long monotonous activity and requires high concentration of attention. Collaborative BCI can help a group of people to interact more effectively by assessing and controlling their physical and/or neurophysiological condition. For example, the assessment of alertness by the collaborative BCI can be used to redistribute the workload among all participants according to their current physiological states to improve overall work efficiency of the group.

In this paper, we propose an approach to collaborative BCI aimed to enhance human-to-human interaction while performing shared visual task. We also describe the setup for such BCI and its possible application in long task of classifying ambiguous visual stimuli with varying degrees of ambiguity by a group of people.

II. Materials and Methods

A. Participants and Experimental setup

Twelve healthy volunteers between the ages of 20 and 45 with normal or corrected-to-normal visual acuity participated in the experiments. All of them provided informed written consent before participating. The experimental studies were performed in accordance with the Declaration of Helsinki and approved by the local Research Ethics Committee of the Innopolis University.

Electroencephalogram signals (EEG) [21] of the subjects were recorded and processed. For EEG recording we used electroencephalograph "Encephalan-EEGR-19/26" made by Medicom MTD (Taganrog, Russia). EEG signals were recorded with sampling rate of 250 Hz and filtered by 50-Hz notch filter and band-pass filter with cutoff frequencies of 1 and 70 Hz. EEG signals were recorded with the help of 31 Ag/AgCl electrodes placed on the scalp in accordance with international scheme "10-10".

B. Visual task

All subjects participated in visual task that consisted in classification of the series of sequentially presented ambiguous (bistable) images. We used the Necker cube [22] as the model for bistable visual stimulus. The Necker cube is a 2D projection of 3D image of a cube with transparent faces and visible ribs. Regular observer sees the Necker cube as a 3D object because of the defined position of the cube edges. Ambiguity in the perception of this cube lies in interpretation of its orientation. The cube can be perceived as left- or right-oriented depending on the contrast of the various internal

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edges of the cube. This contrast parameter $g \in [0, 1]$ can be treated as the degree of complexity of cube's classification and, thus, it can be used as the control parameter. The Necker cubes with a value of g close to 1 or 0 can be easily interpreted as a left- or right-oriented while $g \sim 0.5$ corresponds to the cube with the highest complexity of classification.

C. Data analysis

EEG signals were analyzed with the help of continuous wavelet transform (CWT) [23]. 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 and "*" stands for complex conjugation.

Here we used complex Morlet mother wavelet since it has recommended itself in studies on neurophysiological data [24]–[26]:

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

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

The common way to interpret CWT results is to consider wavelet energy:

$$E(f, \tau) = |W(f, \tau)|^2 \tag{3}$$

Wavelet energy spectrum can also be analyzed in specific frequency band by averaging wavelet energy across this band:

$$E_F(t) = \frac{1}{\Delta f_F} \int_{f \in f_F} E(f, t) df, \tag{4}$$

where Δf_F — width of investigated frequency band.

Averaged wavelet energy $E_F(t)$ can be additionally averaged over some time interval T:

$$e_F = \frac{1}{\Delta T} \int_{t \in T} E_F(t) dt, \tag{5}$$

where ΔT — width of investigated time interval.

In the present study EEG signals were analyzed in alpha and beta frequency ranges during 2-second interval preceding the stimulus presentation and corresponding wavelet energies e_α and e_β were calculated for each presented stimulus (see Eq. 4,5). Wavelet energies were additionally averaged over EEG channels of parietal area.

III. Results

In the present study we aimed to find specific characteristic based on brain activity, that can be used to evaluate attention and, thus, can be used in BCI.

According to multiple reports both α- and β-rhythms are relevant to attention, including visual stimuli processing [27]–[29]. It is well-known that attention modulates the prestimulus α- and β-band power [30], [31] and affects decision accuracy. Thus, either medium or low α- and high β-band power during

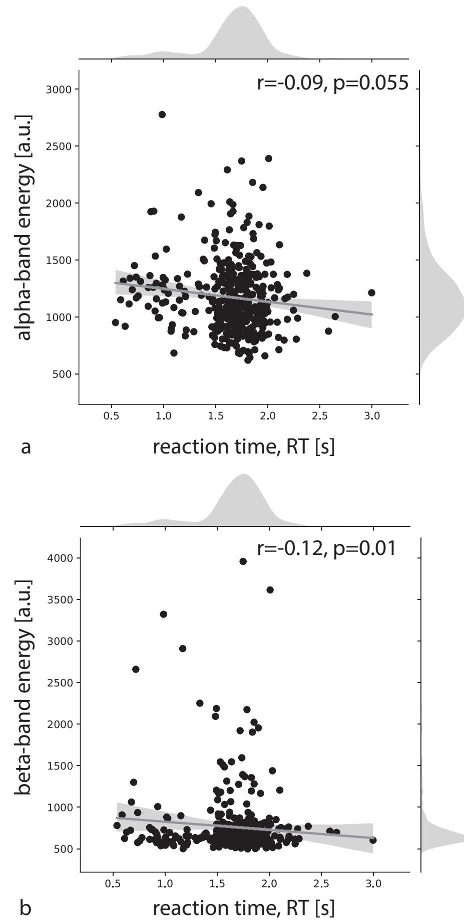

Fig. 1. Correlation between e_α and reaction time RT (a), e_β and reaction time RT (b).

the prestimulus period is beneficial for sensory perception [32]. Thus, to evaluate brain activity related to attention we can use wavelet energies e_α and e_β (see Eq. 4,5). On the other hand, as objective source of information about participant's attention and efficiency in visual task we can use behavioral characteristic — reaction time RT, that reflects time interval between stimulus presentation and subject's response.

In our work we investigated the presence of correlation between e_α and reaction time RT and between e_β and reaction time RT. For this we calculated corresponding Pearson's correlation — results for one of the subjects are shown on Fig.1.

From Fig.1a we can see, that there is no significant correlation between e_α and reaction time RT, however, correlation is more pronounced between e_β and reaction time RT (see Fig.1b). This result suggests that wavelet energy e_β averaged in 2-second prestimulus time interval and over EEG channels of parietal area can be used as a characteristic to assess subject's attention during long classification visual task.

Results, obtained in the present work and our previous studies [33] allow us to propose a design for collaborative BCI aimed to enhance human-to-human interaction while performing shared visual task.

A group of subjects (I — total number of subjects in group) participate in the experiment with such BCI. Each subject have an assigned personal computer for visual stimuli presentation and EEG-recording hardware for data recording, while all client computers are connected to the server that performs all data analysis and overall control on the experimental procedure. Visual stimuli are presented simultaneously for all subjects using specially made software running on the corresponding client computers. According to the value g all the presented stimuli (the Necker cubes) in range $g \in [0, 1]$ can be divided into several groups, that would correspond to different complexity of visual classification task.

Recorded EEG data from each client computer is transmitted to the server, where it is analyzed. The characteristic e_β of each operator is estimated using his/her stimulus-related brain activity preceding each stimulus, then $e_{\beta,i}$ of all subjects are compared ($i = 1, 2...I$ — subjects, number). According to the result of this comparison the server redistributes stimulus complexity between subjects, i.e. the subject with the highest cognitive performance receives stimuli with the highest ambiguity, while subject with the lowest cognitive performance receives stimuli with the lowest ambiguity.

IV. Conclusion

The presented results contributed in the multidisciplinary field of science, especially, in physics and collaborative BCI development. We found specific characteristic based on brain activity in beta-frequency band, that can be used to evaluate attention. We proposed an approach to collaborative BCI using this characteristic. We also described the setup for such BCI and its possible application in long task of classifying ambiguous visual stimuli with varying degrees of ambiguity by a group of people.

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