Approach to collaborative BCI for enhancing human-to-human interaction in shared visual task

Grubov, Vadim, Maksimenko, Vladimir

Vadim V. Grubov, Vladimir A. Maksimenko, "Approach to collaborative BCI for enhancing human-to-human interaction in shared visual task," Proc. SPIE 11847, Saratov Fall Meeting 2020: Computations and Data Analysis: from Molecular Processes to Brain Functions, 118470Q (4 May 2021); doi: 10.1117/12.2591327

Event: Saratov Fall Meeting 2020, 2020, Saratov, Russian Federation

Approach to collaborative BCI for enhancing human-to-human interaction in shared visual task

Vadim V. Grubov, Vladimir A. Maksimenko

Center for Technologies in Robotics and Mechatronics Component, Innopolis University, 1, Universitetskaya Str., Innopolis, 420500, Russia

Saratov State Medical University, 137, Bolshaja Sadovaja Str., Saratov, 410000, Russia

ABSTRACT

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 brain-computer interface. We introduced a characteristic based on prestimulus beta-rhythm activity and proposed an approach to collaborative BCI aimed to enhance human-to-human interaction while performing shared visual task. We also described general 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.

Keywords: brain-brain interface, workload distribution, visual task, visual attention

1. 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.[1–6] 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.[7–9]

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,[10,11] 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[12] or operators of power plants,[13] 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.

Further author information: (Send correspondence to V.V. Grubov)
V.V. Grubov: E-mail: vvgrubov@gmail.com, Telephone: +7 8452 99 88 32

Saratov Fall Meeting 2020: Computations and Data Analysis: from Molecular Processes to Brain Functions, edited by Dmitry E. Postnov, Proc. of SPIE Vol. 11847, 118470Q
 · doi: 10.1117/12.2591327

2. METHODS

Twelve healthy volunteers between the ages of 20 and 45 with normal or corrected-to-normal visual acuity participated in the experiments. None of the subjects had been diagnosed with neurological diseases and did not take medications. The participants were asked to maintain a healthy lifestyle for 48 h before starting the experiment, including 8-hours night rest, refusal on excessive sport exercises, consumption of alcohol and caffeine. The volunteers were informed about design of experiment, its goals, methods and possible inconveniences. They were able to ask any related questions and to receive proper answers. All of the participants provided informed written consent before the start of the experiment. The experimental studies were performed in accordance with the Declaration of Helsinki 1964 and were approved by the local Research Ethics Committee of the Innopolis University.

During the experiment electrical brain activity of subjects was recorded in the form of electroencephalogram (EEG).[14] For EEG recording we used electroencephalograph "Encephalan-EEGR-19/26" made by Medicom MTD (Taganrog, Russia). EEG signals were recorded with special Ag/AgCl electrodes, placed on the subject's scalp. For better conductivity skin was treated with abrasive gel "NuPrep" and electrodes were placed with the help of conductive gel "SuperVisc". During the experiment impedances of EEG electrodes were monitored. Common values of impedance were < 15 Ohm, which is acceptable for proper functioning of EEG electrodes. For EEG recording we used total of 31 EEG electrodes, that were placed in accordance with international scheme "10-10". Ground electrode N was placed above the forehead and referents $A1$ and $A2$ were placed on the left and right mastoids correspondingly.

EEG signals were recorded with sampling rate of 250 Hz and preprocessed. We filtered recorded EEG signals with 50-Hz notch filter and band-pass filter with cutoff frequencies of 1 Hz and 70 Hz. Band-pass filter was implemented to avoid low-frequency and high-frequency noise components related, for instance, to breathing or bad EEG electrode contact. Notch filter was used to remove influence of electric power grid. Additionally, EEG signals were preprocessed with methods of Independent Component Analysis (ICA), since frequency bands of some physiological artifacts (such as cardiac rhythms or eye-movement) overlap informative frequency band of EEG signal. We used ICA to decompose EEG signals into the set of independent components, find components with artifacts, remove them and reconstruct EEG signals with the rest of the components.

All subjects participated in visual task that consisted in classification of the series of sequentially presented ambiguous (bistable) images. We used the Necker cube[15] as the model for bistable visual stimulus and perceptual decision-making.[16,17] 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 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.

EEG signals were analyzed with the help of continuous wavelet transform (CWT).[18,19] The CWT is computed as convolution of EEG signal $x(t)$ with wavelet basis $\varphi_{s,\tau}$:

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

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:[20,21]

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

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 (8–12 Hz) and beta (15-30 Hz) 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.

3. 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.[22–24] It is well-known that attention modulates the prestimulus α- and β-band power[25,26] and affects decision accuracy. Thus, either medium or low α- and high β-band power during the prestimulus period is beneficial for sensory perception.[27,28] 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.

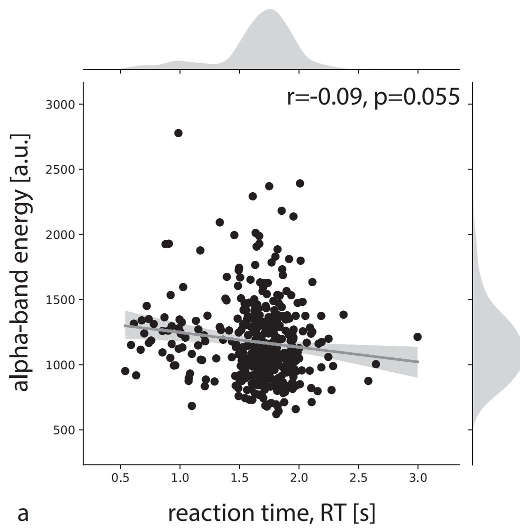
In our work we investigated the presence of correlation between e_α and reaction time RT and between e_β and reaction time RT. For this we calculated corresponding Pearson's correlation — results for one of the subjects are shown on Fig. 1.

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.

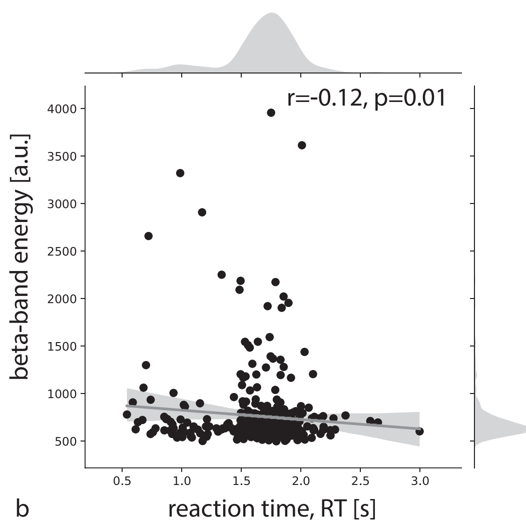
Results, obtained in the present work and our previous studies[29] allow us to propose a design for collaborative BCI aimed to enhance human-to-human interaction while performing shared visual task. The proposed design is illustrated by Fig. 2.

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,



a



b

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

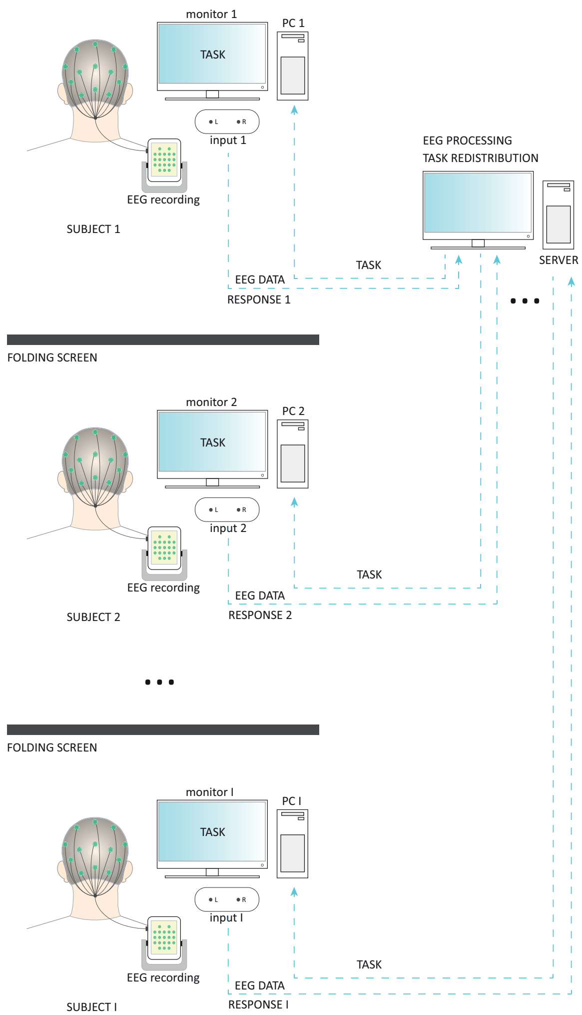


Figure 2. General scheme of experimental setup of brain-to-brain interface.

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.

4. 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.

5. ACKNOWLEDGMENTS

This work was supported by Russian Foundation for Basic Research (Grant 19-32-60033) and by the President's Program (Project NSh-2594.2020.2).

REFERENCES

[1] Chen, X., Wang, Y., Nakanishi, M., Gao, X., Jung, T.-P., and Gao, S., "High-speed spelling with a non-invasive brain–computer interface," *Proceedings of the national academy of sciences* **112**(44), E6058–E6067 (2015).

[2] Bowsher, K., Civillico, E., Coburn, J., Collinger, J., Contreras-Vidal, J., Denison, T., Donoghue, J., French, J., Getzoff, N., Hochberg, L., et al., "Brain–computer interface devices for patients with paralysis and amputation: a meeting report," *Journal of neural engineering* **13**(2), 023001 (2016).

[3] Kawase, T., Sakurada, T., Koike, Y., and Kansaku, K., "A hybrid bmi-based exoskeleton for paresis: Emg control for assisting arm movements," *Journal of Neural Engineering* **14**(1), 016015 (2017).

[4] Spüler, M., "A high-speed brain-computer interface (bci) using dry eeg electrodes," *PloS one* **12**(2), e0172400 (2017).

[5] Maksimenko, V. A., van Heukelum, S., Makarov, V. V., Kelderhuis, J., Lüttjohann, A., Koronovskii, A. A., Hramov, A. E., and van Luijtelaar, G., "Absence seizure control by a brain computer interface," *Scientific Reports* **7**(1), 1–8 (2017).

[6] Hramov, A. E., Grubov, V., Badarin, A., Maksimenko, V. A., and Pisarchik, A. N., "Functional near-infrared spectroscopy for the classification of motor-related brain activity on the sensor-level," *Sensors* **20**(8), 2362 (2020).

[7] Teo, W.-P. and Chew, E., "Is motor-imagery brain-computer interface feasible in stroke rehabilitation?," *PM&R* **6**(8), 723–728 (2014).

[8] Maksimenko, V. A., Hramov, A. E., Grubov, V. V., Nedaivozov, V. O., Makarov, V. V., and Pisarchik, A. N., "Nonlinear effect of biological feedback on brain attentional state," *Nonlinear Dynamics* **95**(3), 1923–1939 (2019).

[9] Frolov, N. S., Pitsik, E. N., Maksimenko, V. A., Grubov, V. V., Kiselev, A. R., Wang, Z., and Hramov, A. E., "Age-related slowing down in the motor initiation in elderly adults," *Plos one* **15**(9), e0233942 (2020).

[10] Wang, Y. and Jung, T.-P., "A collaborative brain-computer interface for improving human performance," *PloS one* **6**(5), e20422 (2011).

[11] Yuan, P., Wang, Y., Wu, W., Xu, H., Gao, X., and Gao, S., "Study on an online collaborative bci to accelerate response to visual targets," in [*2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*], 1736–1739, IEEE (2012).

[12] Sallinen, M., Sihvola, M., Puttonen, S., Ketola, K., Tuori, A., Härmä, M., Kecklund, G., and Åkerstedt, T., "Sleep, alertness and alertness management among commercial airline pilots on short-haul and long-haul flights," *Accident Analysis & Prevention* **98**, 320–329 (2017).

[13] Takahashi, M., Tanigawa, T., Tachibana, N., MUTOU, K., KAGE, Y., SMITH, L., and ISO, H., "Modifying effects of perceived adaptation to shift work on health, wellbeing, and alertness on the job among nuclear power plant operators," *Industrial Health* **43**(1), 171–178 (2005).

[14] Nunez, P. L., Srinivasan, R., et al., [*Electric fields of the brain: the neurophysics of EEG*], Oxford University Press, USA (2006).

[15] Kornmeier, J. and Bach, M., "The necker cubean ambiguous figure disambiguated in early visual processing," *Vision research* **45**(8), 955–960 (2005).

[16] Maksimenko, V. A., Kuc, A., Frolov, N. S., Khramova, M. V., Pisarchik, A. N., and Hramov, A. E., "Dissociating cognitive processes during ambiguous information processing in perceptual decision-making," *Frontiers in Behavioral Neuroscience* **14** (2020).

[17] Hramov, A. E., Frolov, N. S., Maksimenko, V. A., Makarov, V. V., Koronovskii, A. A., Garcia-Prieto, J., Antón-Toro, L. F., Maestú, F., and Pisarchik, A. N., "Artificial neural network detects human uncertainty," *Chaos: An Interdisciplinary Journal of Nonlinear Science* **28**(3), 033607 (2018).

[18] Goswami, J. C. and Chan, A. K., [*Fundamentals of wavelets: theory, algorithms, and applications*], vol. 233, John Wiley & Sons (2011).

[19] Hramov, A. E., Koronovskii, A. A., Makarov, V. A., Pavlov, A. N., and Sitnikova, E., [*Wavelets in neuroscience*], Springer (2015).

[20] Pavlov, A. N., Hramov, A. E., Koronovskii, A. A., Sitnikova, E. Y., Makarov, V. A., and Ovchinnikov, A. A., "Wavelet analysis in neurodynamics," *Physics-Uspekhi* **55**(9), 845 (2012).

[21] Aldroubi, A. and Unser, M., [*Wavelets in medicine and biology*], Routledge (2017).

[22] Linkenkaer-Hansen, K., Nikulin, V. V., Palva, S., Ilmoniemi, R. J., and Palva, J. M., "Prestimulus oscillations enhance psychophysical performance in humans," *Journal of Neuroscience* **24**(45), 10186–10190 (2004).

[23] Gola, M., Magnuski, M., Szumska, I., and Wróbel, A., "Eeg beta band activity is related to attention and attentional deficits in the visual performance of elderly subjects," *International Journal of Psychophysiology* **89**(3), 334–341 (2013).

[24] Baumgarten, T. J., Schnitzler, A., and Lange, J., "Prestimulus alpha power influences tactile temporal perceptual discrimination and confidence in decisions," *Cerebral Cortex* **26**(3), 891–903 (2016).

[25] Anderson, K. and Ding, M., "Attentional modulation of the somatosensory mu rhythm," *Neuroscience* **180**, 165–180 (2011).

[26] Bauer, M., Kennett, S., and Driver, J., "Attentional selection of location and modality in vision and touch modulates low-frequency activity in associated sensory cortices," *Journal of neurophysiology* **107**(9), 2342–2351 (2012).

[27] Van Dijk, H., Schoffelen, J.-M., Oostenveld, R., and Jensen, O., "Prestimulus oscillatory activity in the alpha band predicts visual discrimination ability," *Journal of Neuroscience* **28**(8), 1816–1823 (2008).

[28] Maksimenko, V. A., Runnova, A. E., Frolov, N. S., Makarov, V. V., Nedaivozov, V., Koronovskii, A. A., Pisarchik, A., and Hramov, A. E., "Multiscale neural connectivity during human sensory processing in the brain," *Physical Review E* **97**(5), 052405 (2018).

[29] Maksimenko, V. A., Hramov, A. E., Frolov, N. S., Lüttjohann, A., Nedaivozov, V. O., Grubov, V. V., Runnova, A. E., Makarov, V. V., Kurths, J., and Pisarchik, A. N., "Increasing human performance by sharing cognitive load using brain-to-brain interface," *Frontiers in neuroscience* **12** (2018).