# BCI FOR A BRAIN STATE CONTROL IN A DUAL-TASK PARADIGM

**Vladimir Maksimenko**

Institute of Information Technologies, Mathematics and Mechanics,
Lobachevsky State University of Nizhny Novgorod.
Neuroscience and Cognivite Technology Laboratory,
Center for Technologies in Robotics and Mechatronics Components,
Innopolis University,
Russia.
maximenkovl@gmail.com

## Abstract

The brain resource is limited and it needs to be distributed among the different concurrent tasks. When the subject accomplishes the resource-demanding main task requiring sustained attention, the additional task leads to the reduction of resources allocated for the main task accomplishing. This additional task can be either important or caused by the distraction. Anyway, it causes a performance decrease in the main task. In this paper, we propose a brain-computer interface (BCI) to control the cognitive performance of the visual task accomplishing in the presence of the additional (mental arithmetic) task. We demonstrate how the additional task affects the performance of the main task accomplishing.

## Key words

Brain-computer interface, dual-task paradigm, cognitive resource, visual classification task, mental arithmetic.

## 1 Introduction

The brain resource is limited and it needs to be distributed among the different concurrent tasks [Christie and Schrater, 2015]. According to this, when the subject accomplishes the resource-demanding (main) task requiring sustained attention the (additional) task leads to the reduction of resources allocated for the main task accomplishing. it causes a performance decrease for the main task [Benoit et al., 2019]. In the present work, we study the cognitive performance in the framework of the dual-task paradigm. We use the visual classification task as the main task and the mental arithmetic as an additional task. To monitor the cognitive performance during the main task accomplishing we introduce

a brain-computer interface (BCI) (Fig. 1, A). BCI evaluates the brain activity associated with the visual task accomplishing by estimating the brain response amplitude [Maksimenko et al., 2017]. The high values of the brain response amplitude correspond to the high cognitive performance and vice-versa [Maksimenko et al., 2019]. Using the BCI we analyze, how the cognitive performance of the main task accomplishing is affected by the presence of the additional task.

## 2 Methods

### 2.1 Subjects

Ten healthy subjects, 5 males and 5 females, between the ages of 20 and 28 with normal or corrected-to-normal visual acuity participated in the experiments. All participants were familiar with the experimental task and did not participated in similar experiments in the last 6 months. All participants 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.

### 2.2 Tasks

The subjects performed cognitive tasks in the framework of a dual-task paradigm. The dual-task paradigm requires an individual to perform two tasks simultaneously, to compare their behavioral and cognitive performance with the single-task conditions. In the current research, we used two different tasks. The *main task* consisted in the perception and binary classification of the bistable visual stimuli (Necker cubes) following their interpretations [Kornmeier et al., 2011]. The Necker cube
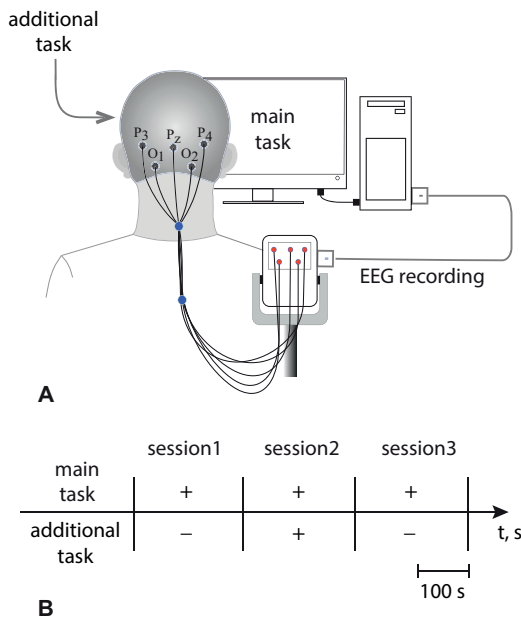
Figure 1. Schematic representation of the proposed brain-computer interface (a) and the experimental session (b).

has transparent faces and visible edges and an observer without any perception abnormalities sees it as a 3D-object due to the specific position of the edges. Bistability in the perception of the Necker cube consists in its interpretation as either left- or right-oriented, depending on the contrast of the inner edges [Grubov et al., 2017]. The Necker cube images with the different inner edges contrast were demonstrated on a $24''$ LCD monitor with a spatial resolution of $1920 \times 1080$ pixels and a 60-Hz refresh rate. Each Necker cube image with black and grey edges was displayed in the middle of a computer screen on a white background The subjects were sitting at a 70–80 cm distance from the monitor with an approximately 0.25-rad visual angle. Each Necker cube was presented for 1-1.5 s. The pause between the subsequent presentations was chosen randomly between 3 and 5 s.

The *additional task* was a mental arithmetics. It implied arithmetical calculations using only the human brain, with no help from any supplies (such as pencil and paper) or devices such as a calculator. In our study, the subjects were asked to sequentially subtract a specific two-digit number (e.g. "27") from a three-digit number (e.g. "1506") in the mind.

## 2.3 Experimental Protocol

Each subject participated in three 4-min subsequent sessions (Fig. 1, B). In the first session, the participant was subjected only to the *main task*. In the second session the *additional task* was performed together with the *main task*. Finally, in the third session the participant was again subjected only to the *main task*.

## 2.4 Recording

To register the EEG data, the cup adhesive Ag/AgCl electrodes were placed on the scalp with the help of

"Tien–20" paste. Before the experiment, we put the abrasive "NuPre" gel on the scalp to increase its conductivity. After the electrodes were installed, we monitored the impedance during the experiments, which varied in the interval of 2–5 k$\Omega$. The ground electrode $N$ was located above the forehead, and reference electrodes $A_1$ and $A_2$ were attached to the mastoids. For filtering the EEG signals, we used a band-pass filter with cut-off points at 0.016 Hz (HP) and 70 Hz (LP), as well as a 50-Hz Notch filter. For EEG and EOG signal amplification and analog-to-digital conversion; the electroencephalograph "Encephalan–EEGR–19/26" ("Medikom-MTD", Taganrog, Russia).

## 2.5 BCI Algorithm

To evaluate the subject's state during the experiment we developed the passive brain-computer interface [Zander and Kothe, 2011]. The BCI algorithm was aimed at estimating the brain response amplitude during the *main task* accomplishing. Based on the previous works [Maksimenko et al., 2018a] we hypothesized that the visual task accomplishing caused an increase of 15-30 Hz-band activity and a decrease of 8-12 Hz activity in the occipital and parietal areas. According to this, we associated the brain response amplitude with the ratio between the EEG spectral amplitude in these bands during the prestimulus and peristimulus period. The brain response amplitude was evaluated in six steps:

**Step 1 – EEG acquisition.** The EEG signals were recorded by the five noninvasive electrodes ($O_1$, $O_2$, $P_3$, $P_4$, $P_z$) with a 250-Hz sampling rate.

**Step 2 – Time-frequency EEG analysis.** We used the continuous wavelet analysis [Hramov et al., 2015]. The wavelet amplitude $E^n(f,t) = \sqrt{W_n(f,t)^2}$ was calculated for each EEG channel $X_n(t)$ in the $f \in [1, 30]$-Hz frequency range. Here, $W_n(f,t)$ is the complex-valued wavelet coefficients calculated as

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

where $n = 1, ..., N$ is the EEG channel number ($N = 5$ being the total number of channels used for the analysis) and "*" defines the complex conjugation. The mother wavelet function $\psi(f,t)$ was the complex Morlet wavelet widely used for the analysis of neurophysiological data and defined as

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

where $\omega_0 = 2\pi$ is the central frequency of the Morlet mother wavelet.

**Step 3 – Extracting spectral components**. In order to follow the dynamics of the main spectral components, we extracted the locations of five of them $(f_1, \ldots, f_5)$

characterized by maximal values of wavelet spectral amplitude $E(f_1), \ldots, E(f_5)$, and then analyzed how the values $f_1, \ldots, f_5$ evolved in time. According to the literature, visual attention during the visual task accomplishing is associated with the interplay between $\alpha$ (8–12 Hz) and $\beta$ (15–30 Hz) frequency bands in occipital and parietal areas. Therefore, we considered the values $f_1, \ldots, f_5$ belonging to these particular frequency bands.

**Step 4 – Quantification of the cognitive performance.** In order to quantify the cognitive performance during the visual stimulus processing, we compared the EEG spectra in the 1-s intervals immediately before and after the onset of stimulus presentation. For this purpose, we calculated the values $A_i^1$, $A_i^2$, $B_i^1$, $B_i^2$ during the presentation of $i$-th stimulus, which statistically described the location of the maximal spectral components using EEG data taken from all occipital and parietal channels before and after the onset of image presentation, as follows:

$$A_i^{1,2} = \sum_{n=1}^{N} \int_{t \in \Delta t_{1,2}^i} \left[ \sum_{k=1}^{K} \xi_k^n(t') dt' \right], \qquad (3)$$

$$B_i^{1,2} = \sum_{n=1}^{N} \int_{t \in \Delta t_{1,2}^i} \left[ \sum_{k=1}^{K} \xi_k^n(t') dt' \right], \qquad (4)$$

where $\xi^n(t) = 1/k$ if $f_k^n \in \Delta f_\beta$ or $\xi^n(t) = 0$ if $f_k^n \notin \Delta f_\beta$. Here, $N = 5$ is the number of EEG channels, $f_k^n$ is the location of $k$-th maximal spectral component, belonging to $n$-th channel, $K = 5$ is the number of analyzed spectral components, and $\Delta t_{1,2}^i$ indicate the 1-s time intervals preceding and following the $i$-th image presentation.

According to the existing works on human attention during the visual information processing, including our recent papers [Maksimenko et al., 2017; Maksimenko et al., 2018b], visual attention is associated with the activation of an "attentional center" in the parietal cortex, which operates at 15–30 Hz frequencies [Laufs et al., 2006], i.e., increased visual attention activates the $\beta$-waves in the parietal area. In addition, visual stimuli processing strengthens connectivity between occipital and parietal areas in $\alpha$ and $\beta$ frequency bands [Michalareas et al., 2016; Buffalo et al., 2011], that in turn causes a growth of $\beta$-activity in occipital cortex. Finally, many studies evidence that visual information processing along with an increase in $\beta$-activity simultaneously inhibits $\alpha$-wave activity. According to our recent study [Maksimenko et al., 2018b], an increase of visual attention causes a percept-related increase in $\beta$-activity with an accompanying decrease in $\alpha$-activity.

Taking into account the above observation, the subject's attention during visual stimulus processing can be quantified as

$$I(t_i) = \frac{(\overline{A}_i^1 - \overline{A}_i^2) + (\overline{B}_i^2 - \overline{B}_i^1)}{2}, \qquad (5)$$

where $\overline{A}_i^{1,2}$ and $\overline{B}_i^{1,2}$ define the values of $A_i^{1,2}$ and $B_i^{1,2}$ averaged over six preceding events ($i - 6, \ldots, i$). Such averaging is performed in accordance with our previous results [Maksimenko et al., 2017], where we demonstrated that when stimuli are processed in a short time, the subject sometimes exhibits low attention $I$ during a single event, even while demonstrating overall high attention during the whole session. One can see that $I(t_i)$ reaches a maximal positive value, if the values in both brackets in Eq. (5) are high and positive. It corresponds to a state of high attention when $\overline{A}_i^1 > \overline{A}_i^2$ and $\overline{B}_i^2 > \overline{B}_i^1$, ii.e., $\alpha$-activity decreases and $\beta$-activity increases. On the contrary, $I(i)$ reaches a minimal negative value when $\overline{A}_i^1 < \overline{A}_i^2$ and $\overline{B}_i^2 < \overline{B}_i^1$. Finally, $I(i)$ is zero when changes in $\alpha$- and $\beta$-activity are insignificant. In the framework of this work, we consider the visual attention as a main indicator of the cognitive performance during the *main task* accomplishing.

## 3 Results

The experimental results are illustrated in Fig 2. The solid curve in Fig. 2, A shows the evolution of the brain response amplitude during the experiment. The vertical dashed lines in Fig. 2, A illustrate the time intervals corresponded to the different sessions. Fig. 2, B demonstrates the mean values of the brain response amplitude for each of the three sessions. The histogram reflects the group means and the error bars define the standard deviation in the group.

One can see that during the first session when the subject performs only the *main task*, $G(t)$ fluctuates near a certain mean value, individual for each subject. Having associated the brain response amplitude $G(t)$ with the cognitive performance, one can conclude, that a mean value of $G$ during the first session characterizes the subject's performance of the *main task* accomplishing.

In the second session, when the *additional task* is performed by the subject together with the *main task*, one can see the significant ($^*p < 0.05$ via Wilcoxon test) decrease of the mean brain response amplitude. It can be supposed, that the presence of the *additional task* causes the cognitive resource reallocation. As a result, the cognitive resource allocated for the *main task* accomplishing is decreased. It, in turn, is reflected in the decrease of the brain response amplitude.

Finally, in the third session $G(t)$ significantly increases for all subjects and reaches the mean value which does not differ significantly from one calculated for the first session. It means that the observed change of the mean brain response amplitude is not associated with the processes like the mental fatigue or the training effect, but caused by the presence of the *additional task*.
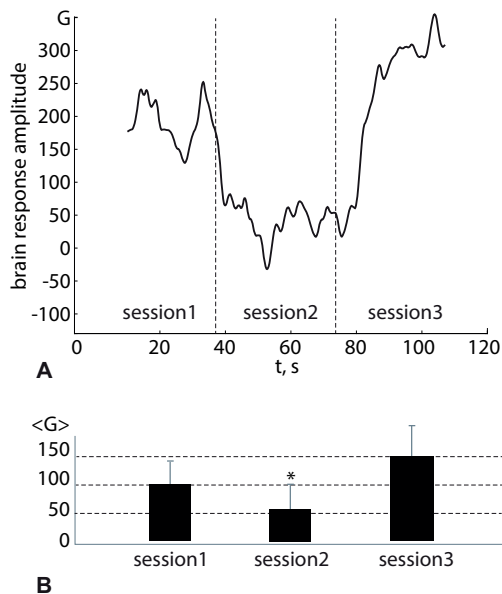
Figure 2. The brain response amplitude vs time during the whole experiment (on the example of the single subject) (a) and mean value of the brain response amplitude for the different sessions (group mean $\pm$SD) (b)

## 4 Conclusion

We have introduced the brain-computer interface to control the cognitive performance of the visual perception task (*main task*) accomplishing in the presence of the *additional task* (mental arithmetic). We demonstrate that the performance of the main task accomplishing decreases in the presence of the additional task. It is important to note that a significant change of the cognitive performance is observed within a relatively short time interval (less than 30 seconds). Thus, the proposed BCI enables detecting the decrease of cognitive performance in real-time. It is important for the sustained attention tasks where the distraction and switching to other tasks causes the decrease of both cognitive and behavioral performance.

From the physical point of view, we demonstrate how the cortical network activity is analyzed by considering the different rhythms of EEG signals. It is known that the brain neuronal network participates in the generation of different rhythms. These rhythms are associated with the synchronization of the neuronal activity in the corresponding frequency bands. The change in the EEG spectral energy in the particular band reflects the degree of neuronal network synchronization. In this context, our results demonstrate the task-related activity in the neuronal network is subserved by the synchronization of high-frequency $\beta$-rhythm whereas the low-frequency $\alpha$-band activity becomes desynchronized.

## References

Benoit, C.-E., Solopchuk, O., Borragán, G., Carbonnelle, A., Van Durme, S., and Zénon, A. (2019). Cognitive task avoidance correlates with fatigue-induced performance decrement but not with subjective fatigue. *Neuropsychologia*, **123**, pp. 30–40.

Buffalo, E. A., Fries, P., Landman, R., Buschman, T. J., and Desimone, R. (2011). Laminar differences in gamma and alpha coherence in the ventral stream. *Proceedings of the National Academy of Sciences*, **108** (27), pp. 11262–11267.

Christie, S. T. and Schrater, P. (2015). Cognitive cost as dynamic allocation of energetic resources. *Frontiers in neuroscience*, **9**, pp. 289.

Grubov, V., Runnova, A., Zhuravlev, M., Maksimenko, V., Pchelintseva, S., and Pisarchik, A. (2017). Perception of multistable images: Eeg studies. *Cybernetics And Physics (6)*, pp. 108–113.

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

Kornmeier, J., Pfäffle, M., and Bach, M. (2011). Necker cube: stimulus-related (low-level) and percept-related (high-level) eeg signatures early in occipital cortex. *Journal of vision*, **11** (9), pp. 12–12.

Laufs, H., Holt, J. L., Elfont, R., Krams, M., Paul, J. S., Krakow, K., and Kleinschmidt, A. (2006). Where the bold signal goes when alpha eeg leaves. *Neuroimage*, **31** (4), pp. 1408–1418.

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. (2018a). Increasing human performance by sharing cognitive load using brain-to-brain interface. *Frontiers in neuroscience*, **12**.

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

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

Maksimenko, V. A., Runnova, A. E., Zhuravlev, M. O., Makarov, V. V., Nedayvozov, V., Grubov, V. V., Pchelintceva, S. V., Hramov, A. E., and Pisarchik, A. N. (2017). Visual perception affected by motivation and alertness controlled by a noninvasive brain-computer interface. *PloS one*, **12** (12), pp. e0188700.

Michalareas, G., Vezoli, J., Van Pelt, S., Schoffelen, J.-M., Kennedy, H., and Fries, P. (2016). Alpha-beta and gamma rhythms subserve feedback and feedforward influences among human visual cortical areas. *Neuron*, **89** (2), pp. 384–397.

Zander, T. O. and Kothe, C. (2011). Towards passive brain–computer interfaces: applying brain–computer interface technology to human–machine systems in general. *Journal of neural engineering*, **8** (2), pp. 025005.