Cognitive interaction via a brain-to-brain interface

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***Abstract*—We developed noninvasive brain-to-brain interface for dynamical redistribution of cognitive load between subjects according to their current performances during shared cognitive task. As a result, a participant who exhibits higher cognitive performance is subjected to a higher workload, while his/her partner receives a lower workload. We demonstrate that dynamical workload redistribution allows to increase overall cognitive performance in the pair of interacting subjects.**

***Index Terms*—electroencephalogram, brain-to-brain interface, cognitive performance, cognitive load, cognitive resource**

I. Introduction

Complex cognitive task requires to involve neuronal populations in the different cortical regions [1]. During the accomplishment of a prolonged and resource-demanding task the neuronal populations need to maintain cognitive performance at a certain level to ensure high behavioral performance. As the result, such demanding tasks cause mental fatigue accompanied by subjective feeling of exhaustion and cognitive decline [2]. Along with the fatigue, the cognitive performance can be defined by the human personality [3], the initial motivation [4], training effect [5] and the task complexity. Many of these features can be evaluated through analysis of electric brain activity, thus opening opportunity to estimate cognitive performance. This underlies the possibility of the passive brain-computer interfaces for the cognitive activity evaluation and training [6].

In the present work we demonstrate that the cognitive performance during the visual classification task accomplishing can be increased due to the cognitive interaction with another human via a brain-to-braininterface (BBI) [7]. Using the BBI we analyze the cognitive interaction between the partners subjected to the visual classification task. Having compared the experimental sessions with different interaction protocol we report the most optimal interaction configuration resulting in the increase of the cognitive performance.

II. Methods

20 healthy unpaid volunteers, 12 males and 8 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. The experimental studies were performed in accordance with the Declaration of Helsinki.

The cognitive task was to classify the consistently presented ambiguous Necker cubes [8]. We used two subsets: the cubes of the high complexity of interpretation (HC) for $g \sim 0.5$ and the cubes of low complexity of interpretation (LC) for $g \sim 0$ and $g \sim 1$. During the experimental session, the Necker cubes with the randomly chosen ambiguity were presented for 300 times. The presentation time was in range of 1-1.5 sec with the pause between presentations of 3-5 s.

To register the EEG data, we used electroencephalograph "Encephalan-EEG-19/26" with cup adhesive Ag/AgCl electrodes placed on the "Tien–20" paste. The EEG signals were filtered by a band-pass filter with cut-off points at 1 Hz (HP), as well as a 100 Hz (LP) and a 50-Hz Notch filters. The

Similarly to the recent work [9], we analyze 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, using the continuous wavelet transform [10].

Each event associated with the presentation of a single visual stimulus is analyzed separately in the 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 is sent by the software together with the presentation of the stimuli initiated the calculation.

As a result, the set of values A_i^1, A_i^2, B_i^1, B_i^2 characterizing the stimulus-related brain response in the α (8-12 Hz) and β (15-30 Hz) frequency bands are calculated for i-th presentation as

$$A_i^{1,2} = \sum_{n=1}^{N} \int_{t \in \tau_i^{1,2}} \sigma_\alpha^n(t')dt', \tag{1}$$

$$B_i^{1,2} = \sum_{n=1}^{N} \int_{t \in \tau_i^{1,2}} \sigma_\beta^n(t')dt', \tag{2}$$

where

$$\sigma_\alpha^n(t) = \begin{cases} 1, & \text{if} \quad f_{max}^n \in \Delta f_\alpha, \\ 0, & \text{if} \quad f_{max}^n \notin \Delta f_\alpha. \end{cases} \tag{3}$$

and

$$\sigma_\beta^n(t) = \begin{cases} 1, & \text{if} \quad f_{max}^n \in \Delta f_\beta, \\ 0, & \text{if} \quad f_{max}^n \notin \Delta f_\beta, \end{cases} \tag{4}$$

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

The control characteristic $H(i)$ is calculated by averaging $A_i^{1,2}$ and $B_i^{1,2}$ values over 6 presentations.

The value of $H(i)$ calculated in real time, reflects the intensity of the brain response on the appearing visual stimuli. Large $H(i)$ is associated with a high response due to more careful image processing by the subject, whereas small $H(i)$ is associated with a low response, which takes place when the subject does not pay much attention on the classification task.

The values $H_{1,2}$ characterizing the cognitive performance of the subjects were compared at every moment. If the cognitive performance H_1 of the subject 1 exceeds the cognitive performance H_2 of the subject 2, the subject 1 gets the stimuli with high ambiguity, whereas the subject 2 gets the stimuli with low ambiguity.

III. Results

The subject's cognitive performance has been measured based on the brain-response amplitude H (see methods). The larger values of the brain response amplitude have been associated with high cognitive performance and vice versa. The mean cognitive performance has been calculated as H, averaged over the experimental session.

The subjects participated in two experiments consisting of two sessions. In the first sessions, each participant was subjected to the whole set of stimuli. In the second session, the stimuli with different ambiguity (the cognitive load) were distributed according to the subjects' cognitive performances. The structure of the second session was different in the experiment 1 and experiment 2. In the experiment 1 the cognitive load was redistributed based on the comparison of the instant values of the cognitive performance. In the experiment 2 the cognitive load redistribution was performed by comparing the cognitive performances averaged over the certain time interval t_0. Following our work [7], the time interval length was specified as one associated with the presentation of 20 stimuli.

The cognitive performances of interacting subjects were compared between the different sessions. As the result, the cognitive performances of both subjects did not differ for the first session of experiment 1 and experiment 2 ($p > 0.05$ via paired samples t-test). For the second session we observed the significant increase of the cognitive performance (mean in pair) in the second experiment when compared with the first experiment ($^*p < 0.05$ via paired samples t-test). The obtained result demonstrates that the cognitive load redistribution is more active when performed based on the comparison the averaged cognitive performances.

IV. Conclusion

The recent studies report that the cognitive performance during the cognitive task accomplishing is not maintained at a constant level but fluctuates in time. During the prolonged cognitive task accomplishing the mean value of the cognitive performance is determined by the cognitive resource. Since the cognitive resource is limited, the cognitive performance cannot be enhanced immediately and requires a systematic training. In this context, the present work demonstrates that the cognitive performance can be also increased as the result of cognitive interaction via the BBI enabling the cognitive load distribution across the subjects.

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