Cognitive interaction during a collaborative attentional task

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***Abstract*—The modern trend in neuroscience and engineering is the developing systems allowing increase human physical and cognitive abilities through human-machine interaction. In these systems the human's condition is controlled by a brain-computer interface and assistance is activated when cognitive (or physical) performance decreases. In the current paper we consider the system, where the human's cognitive performance is enhanced due to cognitive interaction with another human. The proposed interface was tested at experimental sessions, in which the subjects were asked for a long time to solve the problem of classification of ambiguous visual stimuli of varying complexity. The proposed interface allows to increase the average productivity of a group of people due to the distribution of cognitive load between all participants.**

Keywords—brain-brain interface, workload distribution, visual task, visual attention, mental fatigue.

I. Introduction

One of the main practical tasks of modern neuroscience is the development of brain-computer interface (BCI). This interface can be used for rehabilitation medicine and for healthy subjects to enhance their cognitive abilities in solving task under high mental workload. During the last years, along with BCI, the brain-to-brain interfaces (BBI) were proposed to enable direct information transfer between the brains of interacting humans and animals.

BBI can be useful for improving the cognitive performance of a group of people subjected to a common work task that requires sustained attention and alertness. For example, pilots of military [1] or civil aircraft [2] or operators of power plants [3,4], whose work is associated with a long monotonous activity and requires high concentration of attention [5]. Brain-brain interface can help a group of people interact more effectively by assessing and controlling their physical condition. For example, as a result of the assessment of the degree of alertness by the BBI, workload can be distributed among all participants depending on their current physiological state.

In this paper, we propose a BBI to enhance human-human interaction while performing collective tasks. The proposed brain-brain interface is tested during experimental sessions in which participants perform the long task of classifying ambiguous visual stimuli with varying degrees of ambiguity.

II. Materials and Methods

A. Participants

Twenty healthy volunteers, twelve males and eight females, between the ages of 20 and 43 with normal or corrected-tonormal 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.

B. Visual task

Visual task consisted in classification of the sequentially presented ambiguous Necker cubes as left- or right-oriented. The Necker cube [6] is a 2D-image which looks like a cube with transparent faces and visible ribs.

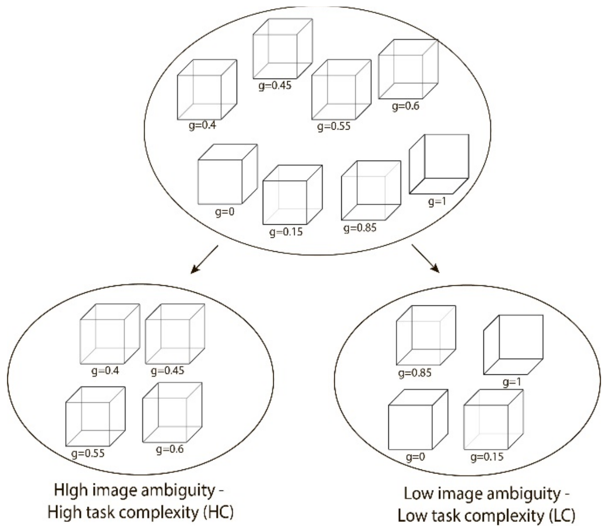

Fig.1. The examples of presented Necker cube images with different values of control parameter *g*. Two sets of visual stimuli: with a high degree of ambiguity, representing a task of high complexity (HC) and with a low degree of ambiguity, representing a task of low complexity (LC)

An 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 is to interpret it as oriented to the left (g=0) or to the right (g=1) depending on the contrast of the various internal edges of the cube. The value of g is considered as the degree of complexity of this classification. Necker cubes with a value of g close to 1 or 0 can be easily interpreted as a left- or right-oriented. the whole set of presented stimuli was divided into two subtasks: the task of high complexity of interpretation with (HC) and the task of low complexity of interpretation with (LC) (Fig. 1) [7,8].

C. Experimental setup and design

The experimental setup is demonstrated in Fig. 2. Visual stimuli were simultaneously presented to a pair of participants (subject 1 and subject 2) using a special software running on the corresponding client personal computers. During these presentations, the EEGs of the subjects were recorded and processed. The performance of each operator was estimated

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using his/her stimulus-related brain response $I(i)$ to every presented i-th stimulus.

The brain responses $I_1(i)$ and $I_2(i)$ of subject 1 and subject 2, respectively, were compared. Depending on the result of this comparison, the control command, the ambiguity range of Necker cubes was corrected for each subject. For example, if $I_1(i) > I_2(i)$, then subject 1 received a stimulus with higher ambiguity, while subject 2 perceived a stimulus with weaker ambiguity.

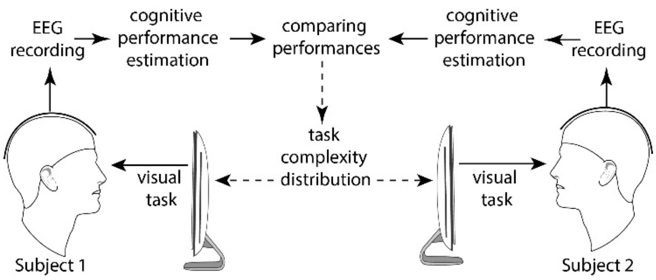

Fig.2. Schematic illustration of experimental setup

The subjects were randomly divided into 10 pairs and participated in two sets of experiments. The both sets contained two sessions, session 1 and session 2, each lasted 30 minutes. During session 1 in both experiments the cubes with different parameters g were randomly presented to the participants. Each stimulus was presented about 30 times. During the session 2 of the first experiment the cubes were demonstrated in a similar way with the session 1. During the session 2 of the second experiment, the whole set was divided into high ambiguity (HC) and low ambiguity (LC) stimuli sets (Fig. 1). These different sets of stimuli were presented to the participants according to their brain responses amplitude. Namely, a subject whose brain response amplitude exceeded one calculated for his/her partner got stimuli with higher ambiguity.

The brain response amplitude was estimated based on the spectral properties of EEG signals recorded using five electrodes located in parieto-occipital cortices [9]. EEG spectra were analyzed via the wavelet transformation [10-11]. EEG signals were analyzed in alpha and beta frequency ranges at 1 second interval preceding the stimulus presentation and following the moment of stimulus appearance. Electrical brain activity in alpha and beta bands is associated with visual attention and stimuli processing [12]. Brain response I was estimated for each image i via the ratios of wavelet energies in alpha and beta bands before and after the stimulus presentation. The high brain response amplitude was achieved when alpha rhythm energy exhibited decrease after stimulus presentation and beta rhythm energy increased.

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

III. Results

Average individual performance $\langle I_{1,2}\rangle$ was calculated for each session. This characteristic was calculated for each subject by averaging his/her brain response $I(i)$ more than 200 demonstrations of the Necker cube. Then, individual performance $\langle I_{1,2}\rangle$ of both subjects in the pair were averaged to assess the performance of the pair $\langle I_{pair}\rangle$.

Fig. 3 presents the results of comparing the two sets of experiments. The results are presented in the form of box-and whiskers diagrams which show average performance $\langle I_{pair}\rangle$ in all pairs. It is seen that during the first experiment (a) a pair's response did not changed between sessions. However, a significant increase is observed during the session 2 of the second experimental set (b).

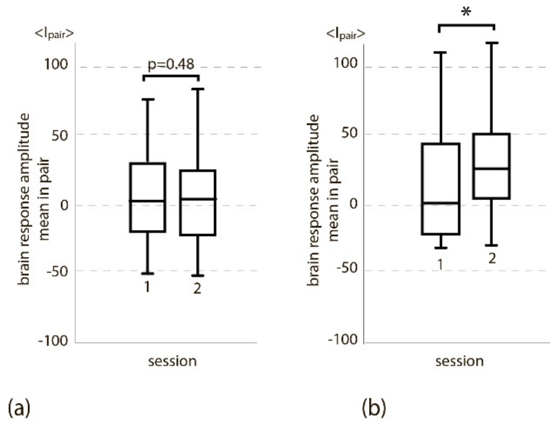

Fig.4. (a) Brain response amplitude mean in pairs $\langle I_{pair}\rangle$ during the first (a) and the second (b) experiments for session 1 and session 2. (*$p < 0.05$ by paired sample t-test, the compared distributions are tested with Shapiro Wilk normality test).

IV. Conclusion

In this paper, we the brain-to-brain interface in which a cognitive performance is enhanced through cognitive interaction between humans. It should be noted that the study of the possibility of human interaction through the brain-brain interface was carried out in other works [13]. It was proposed to transmit motor information registered in the cortical region directly to the motor area of the cerebral cortex of another person by means of brain stimulation [14-18]. However, this system did not improve performance, because it did not take into account the state of the brain of interacting people. The proposed system can be used in cases where cognitive or physical activity should be unevenly distributed among the participants in accordance with their current psychophysiological conditions, such as aircraft pilots or nuclear power plant operators

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