Brain-to-brain interface increases efficiency of human-human interaction

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***Abstract*—We propose a special brain-brain interface (BBI) to enhance human-human interaction while performing collective tasks. The efficiency of the proposed interface is estimated in experimental sessions, where participants are subjected to the prolonged task of classification of ambiguous visual stimuli with different degrees of ambiguity. Our BBI allows increasing the mean working performance of a group of operators due to optimal real-time redistribution of a cognitive load among all participants, so that the more difficult task is always given to the member who exhibits the maximum cognitive performance. We show that human-human interaction is more efficient in the presence of the coupling delay determined by brain rhythms of the participants.**

***Index Terms*—Brain-brain interface, human-human interaction, workload distribution, mental fatigue, visual task, visual attention.**

I. Introduction

The main goal of a brain-computer interface (BCI) is to repair or increase human performance in solving cognitive tasks. In this particular case, the machine being controlled by human's brain activity, assumes a part of the cognitive or physical human load. The feedback information acquired from sensors allows controlling the machine power in accordance with the workload subjected by the human.

Similarly to the human-machine interaction, a human-human interaction can be improved by a brain-brain interface (BBI). In this situation, the machine component of traditional BCI can be replaced by another human linked to the first one by the interface which assistance enhances the subject performance in managing a particular task. This would be very helpful for a group of people subjected to a common job task which requires sustained attention and alertness. In every day practice, this is a common occurence, for example, among pilots of a military [1] or a civil aircraft [2], or a power plant operators, whose routine work includes continuous monitoring of instrument readings, that requires sustained alertness and concentration [3]–[5]. A human-human interface could help such people to have effective interactions by estimating and monitoring physical conditions of each person, in particular, degree of alertness, in order to distribute workloads among all participants according to their current physiological status.

In this paper, we propose a special BBI to enhance human-human interaction while performing collective tasks. The efficiency of the proposed BBI is estimated in experimental sessions, where participants are subjected to the prolonged task of classification of ambiguous visual stimuli with different degrees of ambiguity.

II. Methods

A. Subjects

Twenty healthy volunteers, twelve males and eight 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 and approved by the local research Ethics Committee.

B. Visual task

All participants were subjected to the visual task of classification of consistently presented ambiguous Necker cubes which can be interpreted as left- or right-oriented (Fig. 1(a)). The Necker cube [6] is a 2D-image which looks like a cube with transparent faces and visible ribs. An observer without any perception abnormalities perceives the Necker cube as a bistable 3D-object due to the specific position of the cube's ribs. Bistability in perception consists in the interpretation of this cube as to be either left- or right-oriented depending on the contrast of different inner ribs. The contrast $g \in [0,1]$ of the three middle lines centered in the left middle corner was used as a control parameter [7]. The cube's ambiguity is characterized by parameter $g = y/255$, where y is the brightness of the middle lines according to the 8-bit grayscale palette. The values $g = 1$ and $g = 0$ correspond, respectively, to 0 (black) and 255 (white) pixels' luminance of the middle lines.

The value of g is considered as the degree of complexity of this classification. One can see that unlike the cases when g is close to 0.5, the images for which g is close to 1 or 0 can be easily interpreted as left- or right-oriented cubes, respectively. According to the classification task, the whole set of presented stimuli $g = (0; 0.15; 0.4; 0.45; 0.55; 0.6; 0.85; 1)$ is split into two subtasks: the task of high complexity for highly ambiguous images with $g = (0.4; 0.45; 0.55; 0.6)$ and the task of low complexity for weakly ambiguous cubes with $g = (0; 0.15; 0.85; 1)$ (Fig. 1(b).

C. Experimental design

All participants were instructed to press either left or right key depending on their first impression of the cube orientation at each presentation. The subjects were randomly divided into 10 pairs and participated in two sets of experiments, without coupling delay and with delay in the coupling. The both sets contained two sessions, session 1 and session 2, each lasted 30 minutes. During the first session, the cubes with different g were randomly selected from the whole set of stimuli, and each stimulus was presented about 30 times. During the second session, the whole set of stimuli was split into two sets, the stimuli with high ambiguity (HC) and the stimuli with low ambiguity (LC). 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.

D. Estimation of the brain response

We analyzed 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 [8], using the continuous wavelet transform [9]. The wavelet energy spectrum $E^n(f,t) = \sqrt{W_n(f,t)^2}$ 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

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

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 $\psi(f,t)$ is the Morlet wavelet often used for the analysis of neurophysiological data defined as

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

where $\omega_0 = 2\pi$ is the central frequency of the Morlet mother wavelet [10].

Each event associated with the presentation of a single visual stimulus was analyzed separately in the alpha and beta frequency bands on a 1-s interval preceding the image presentation and followed by the moment of the stimulus appearance. Electrical brain activity in alpha and beta bands is associated with visual attention and stimuli processing [11]. A special digital trigger was 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 were calculated for i-th presentation as follows

$$A_i^{1,2} = \sum_{n=1}^{N} \int_{t\in\tau_i^{1,2}} \xi^n(t')dt', \text{ where} \quad (3)$$

$$\xi^n(t) = \begin{cases} 1, & \text{if} \quad f^n_{max} \in \Delta f_\alpha, \\ 0, & \text{if} \quad f^n_{max} \notin \Delta f_\alpha. \end{cases} \quad (4)$$

$$B_i^{1,2} = \sum_{n=1}^{N} \int_{t\in\tau_i^{1,2}} \xi^n(t')dt', \quad (5)$$

$$\text{where} \quad \xi^n(t) = \begin{cases} 1, & \text{if} \quad f^n_{max} \in \Delta f_\beta, \\ 0, & \text{if} \quad f^n_{max} \notin \Delta f_\beta, \end{cases} \quad (6)$$

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

The obtained values were averaged over 6 presentations, and then the control characteristic $I(i)$ was calculated as

$$I(i) = \frac{(a_i^1 - a_i^2) - (b_i^2 - b_i^1)}{2}, \quad (7)$$

where $a_i^{1,2}$ and $b_i^{1,2}$ were obtained as

$$a_i^{1,2} = \frac{1}{6} \sum_{n=i-6}^{i} A_n^{1,2}, \quad (8)$$

$$b_i^{1,2} = \frac{1}{6} \sum_{n=i-6}^{i} B_n^{1,2} \quad (9)$$

by averaging $A_i^{1,2}$ and $B_i^{1,2}$ values over 6 presentations.

The value of $I(i)$ calculated using Eqs. (3-7) 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.

E. Experimental setup

The experimental setup is demonstrated in Fig. 1(c). The ambiguous visual stimuli (Necker cubes) with different degree of ambiguity were consistently presented to participants who had to classify them. The complexity of the task was determined by the degree of ambiguity; the higher the ambiguity, the greater the observer's attention. First, each stimulus was simultaneously presented to a pair of operators (subject 1 and subject 2) using a special software running on the corresponding client personal computers (PC1 for subject 1 and PC2 for subject 2). During these presentations, the subjects' EEGs were simultaneously recorded and transmitted in real time to the corresponding PCs. The performance of each operator was estimated using his/her stimulus-related brain response $I(i)$ to every presented *i*-th stimulus. The analysis was carried out on the base of the EEG spectral properties.

The brain responses $I_1(i)$ and $I_2(i)$ of subject 1 and subject 2, respectively, were transmitted to the computational server for the comparative analysis of the signals obtained for every presented *i*-th stimulus. Depending on the result of this comparison, the corresponding control command was sent to each PC to adjust the ambiguity range of the presented stimuli for each subject. For example, if $I_1(i) > I_2(i)$, then subject 1 received a stimulus with higher ambiguity, while

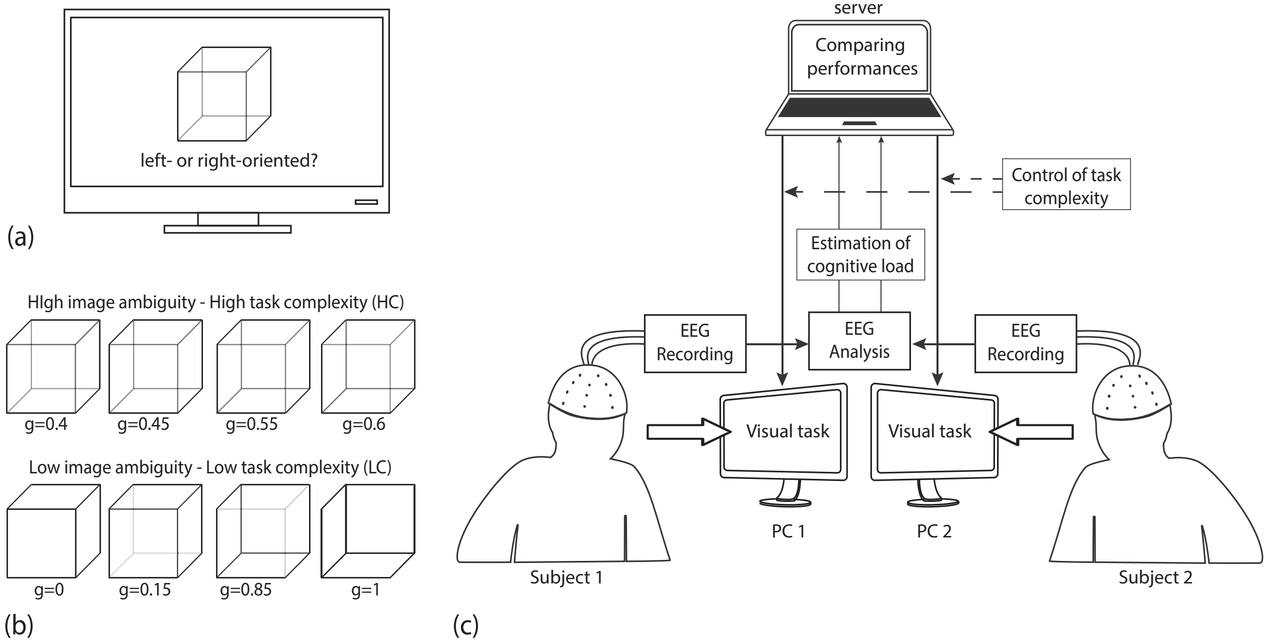

Fig. 1. (a) Visual task illustration. (b) Whole set of visual stimuli split into two sets: (upper row) cubes with high degree of ambiguity representing the task of high complexity (HC) and (lower row) cubes with low degree of ambiguity representing the task of the low complexity (LC). (c) Schematic illustration of the brain-brain interface.

subject 2 perceived a stimulus with weaker ambiguity. Thus, the feedback signal from the computational server managed the task handout depending on the stimuli complexity and the operator's performance.

III. Results

The proposed BCI was tested in two sets of experiments. During the first set of experiments, a pair of participants interacted through a non-delayed coupling, i.e., the task complexity was distributed among the participants based on their instantaneous alertness; the partner with higher alertness received a higher complexity task, while another partner was tasked with lower complexity. Unlike the first set of experiments, during the second set we introduced a delay in the coupling between the participants. If the difference between their degrees of alertness became larger than 10%, the partner with greater alertness received a higher complexity task. Both sets of the experiments were preceded by the non-coupled session, during which both subjects received the whole set of stimuli, i.e., the degree of image ambiguity was randomly chosen from the range $[0, 1]$, and the feedback signal from the computational server was absent. In this preliminary experimental session, the individual brain response level was measured before the coupling was applied.

For each session, the average individual performance $\langle I_{1,2} \rangle$ was calculated for each subject by averaging his/her brain response $I(i)$ over 200 image presentations. Then, $\langle I_{1,2} \rangle$ of both subjects in the pair were averaged in order to estimate the pair's performance $\langle I_{\mathrm{pair}} \rangle$.

The results of the comparison between two sets of the experiments are presented in Fig 2 in the form of box-and-

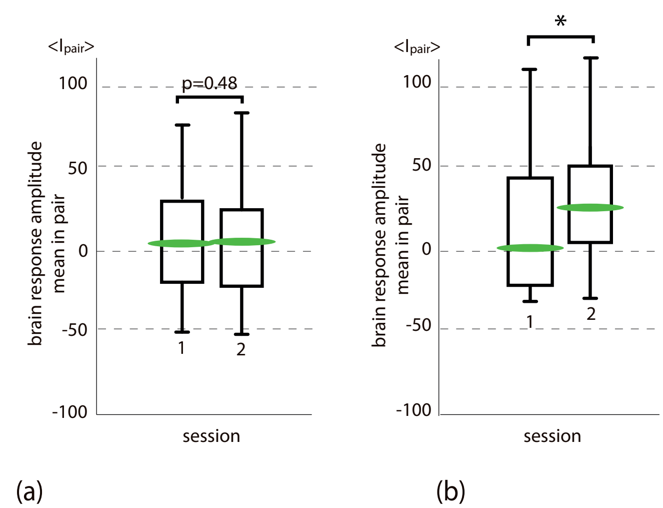

Fig. 2. (a) Mean brain response $\langle I_{\mathrm{pair}} \rangle$ for pairs during the first set of experiment: session 1 (no link between subjects, $p = 0.979$ by ShapiroWilk normality test) and session 2 (no delay in coupling between subjects, $p = 0.847$ by Shapiro-Wilk normality test) (not significant, $n = 10$, $p = 0.48$ by paired sample t-test). (b) Mean brain response $\langle I_{\mathrm{pair}} \rangle$ for pairs during the second set of experiments: session 1 (no link between subjects, $p = 0.108$ by Shapiro-Wilk normality test) and session 2 (no delay in coupling between subjects, $p = 0.622$ by ShapiroWilk normality test) (significant change, $n = 10$, $^*p < 0.05$ by paired sample t-test). Medians (green bars), $25 \div 75$ percentiles (box) and outlines (whiskers) are shown.

whiskers diagrams which show average performance $\langle I_{\mathrm{pair}} \rangle$ in all pairs. One can see that according to the group analysis, the interaction between subjects during the first experimental set (Fig 2(a)) did not bring a significant effect on the degree of their performance. On the contrary, we uncovered a significant increase in the degree of pair's alertness in the second experimental set (Fig 2(b)), where the task complexity was changed as soon as a 10% difference appeared between the values of $I_1(i)$ and $I_2(i)$.

IV. Discussion

In order to explain the obtained result, let us consider the evolution of the brain response during one experimental session. The dependence $I(i)$ illustrates a change in the amplitude of the brain response as the number of presented Necker cubes i is increased. This dependence exhibits oscillations whose period varies from 15 to 40 presented stimuli (solid curves in Fig. 3). Such oscillatory behavior of the brain response can be associated with the existence of the brain restoration state caused by relaxation oscillations of the neural ensemble. The black and green curves in Fig. 3 correspond to the dependences $I(i)$ calculated for the subjects in pair during the second session of the first (a) and second (b) set of the experiments. The lower traces show switches between presentations of two sets of visual stimuli (high ambiguous and low ambiguous), i.e., switches of the task complexity.

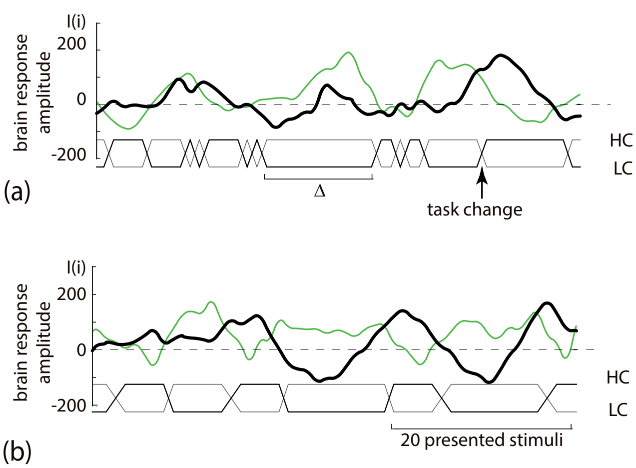

Fig. 3. Results of the (a) first and (b) second sets of experiments. (Upper traces) Brain responses of each subject in the pair ($I(i)$). (Lower traces) Switches between two sets of visual stimuli (HC and LC). The arrow shows a single switch of the task change. The length of the interval (Δ) between two successive switches is measured in the number of presented stimuli.

One can clearly see in Fig. 3(a), that during the first experimental set, where the task complexity was switched immediately as soon as the amplitude of the brain response of one subject ($I_1(i)$) exceeded the brain response of another subject ($I_2(i)$), there are many frequent switches with $\Delta < 5$, smaller than the average period of $I(i)$ oscillations. In this case, the dependencies $I_1(i)$ and $I_2(i)$ obtained for two subjects do not demonstrate an antiphase mode. On the contrary, in the second experimental set (Fig. 3(b)), the values of $I(i)$ obtained for two subjects behave mostly in antiphase and therefore the switches are not so frequent.

One can conclude that in the first experimental set, the multiple unnecessary spontaneous switches caused by high-frequency fluctuations of $I(i)$, interfered with the establishment of an antiphase mode between oscillations of the values of I_1 and I_2 of the subjects in the pair. During the second experimental set, such switches appeared more scarcely and the interval Δ between two successive switches matched the period of the $I(i)$ oscillations, which was estimated to be varied from 15 to 40 stimuli presentations. Taking into account that the period of $I(i)$ oscillations appeared in the same range, we can conclude that the switching regime in the second set of the experiments mostly satisfies the criteria described above, and therefore leads to an increase in pair's performance.

V. Conclusion

In this paper, we have demonstrated, for the first time to the best of our knowledge, the possibility to increase human cognitive performance due to assistance of another human by sharing a cognitive load between them using a brain-brain interface.

Having analyzed the mean degree of alertness in these experiments, we have found that increasing alertness was only observed in the experiment where the task complexity was changed as soon as the difference in the degree of alertness between the partners exceeded 10%. We have shown that this effect is caused by the oscillatory behavior of the degree of alertness, where the oscillation period is determined by the brain restoration. In this respect, the effective interval of the change in the task complexity coincides with such brain rhythm.

It should be noted that human-human interaction has recently become a very hot topic in neuroscience, physics and IT-technologies. In particular, the possibility of human-human interaction via BBI was demonstrated in a way, where motor information registered in the cortical region was transmitted to the motor cortex region of another subject via brain stimulation [12]–[15]. Although this BBI transmitted information directly from brain to brain, it did not improve their working performance. The control command was translated to the receiver's brain in any case, regardless the willingness to perform the action. In other words, the previous BBI system did not take into account the brain states of interacting people.

Instead, our BBI analyzes and compares human brain states in order to enhance their working performance in tasks which require sustained attention. This is a core feature of human-human interaction. Possible applications of the proposed BCI are widespread, from aircraft pilots to nuclear plant operators, in all cases where a cognitive or physical load needs to be unequally distributed among participants according to their current psychophysiological conditions.

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