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Cognitive interaction via a brain-to-brain interface

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ABSTRACT

We develop a noninvasive brain-to-brain interface, which enables a dynamical redistribution of a cognitive workload between subjects based on their current cognitive performances. As a result, a participant who exhibits a higher performance is subjected to a higher workload, while his/her partner receives a lower workload. We demonstrate that the workload distribution allows increasing cognitive performance in the pair of interacting subjects.

Keywords: brain-to-brain interface, cognitive performance, cognitive load, cognitive resource.

1. INTRODUCTION

During accomplishing a cognitive task brain involves the neuronal populations in the different cortical regions.[1] In this context, accomplishing a prolonged and resource-demanding task requires the neuronal populations to maintain a cognitive performance at a certain level to ensure high behavioral performance. Prolonged resource-demanded 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 features of human personality,[3] the initial motivation,[4] training effect[5] and the task complexity. The possibility to relate the cognitive performance with the specific features of the noninvasive electroencephalograms enables the objective evaluation of the human cognitive performance and the prediction of behavioral performance. This underlies the functioning of the passive brain-computer interfaces for the cognitive activity evaluation and training.[6] According to the recent studies, the cognitive performance can be enhanced as the result of systematic training.[7] At the same time, the cognitive performance cannot be increased immediately due to the cognitive resource limitation.[8]

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 brain-interface (BBI).[17] 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 resulting in the increase of the cognitive performance.

2. METHODS

2.1 Experimental procedure

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 and approved by the local research Ethics Committee of the Innopolis University.

The cognitive task was to classify the consistently presented ambiguous Necker cubes as left- or right-oriented. The Necker cube is a 2D-image which is perceived by the observer as a bistable 3D-object due to the specific position of the inner edges. Bistability in perception consists in the interpretation of this 3D-object as to be either left- or right-oriented depending on the contrast $g \in [0, 1]$ of the three middle lines centered in the left middle corner. The value $g = y/255$ defines the Necker cube ambiguity which, in its turn, is associated with

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the complexity of its interpretation. If g is close to 0 or 1 the Necker cube can be easily interpreted as the left- or the right-oriented 3D-object. When approaching $g = 0.5$, the stimulus becomes ambiguous resulting in the increased complexity of its correct interpretation.[9] According to this, we divided the whole set of the Necker cubes into 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 by an observer 300 times. The presentation time was randomly chosen from the range 1-1.5 sec and the pause between the presentation was 3-5 s.

To register the EEG data, we use cup adhesive Ag/AgCl electrodes placed on the "Tien–20" paste. Immediately before the experiments started, we perform all necessary procedures to increase the conductivity of the skin and to reduce its resistance using abrasive "NuPrep" gel. The impedances are monitored after the electrodes are installed, and measured during the experiments. Usually, the impedance values vary within the 2–5 kΩ interval. The ground electrode N is located in front of the head at the Fpz electrode location. The EEG signals are 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 electroencephalograph Encephalan-EEG-19/26 (Medicom MTD company, Taganrog, Russian Federation).

2.2 Cognitive performance estimation

Similarly to the recent work,[10] 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.[11] The electrodes location was specified in accordance with the visual and attentional centers location.[12] The wavelet energy spectrum $E^n(f,t) = \sqrt{W_n(f,t)^2}$ is calculated for each EEG channel $X_n(t)$ in the $1 - 30$ Hz frequency range. Here, $W_n(f,t)$ is the complex-valued wavelet coefficients calculated as

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

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

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

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

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[13] are calculated for i-th presentation as

$$A_i^{1,2} = \sum_{n=1}^{N} \int_{t \in \tau_i^{1,2}} \xi_\alpha^n(t')dt', \tag{3}$$

where

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

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

where

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

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

The obtained values are averaged over 6 presentations and control characteristic $I(i)$ is calculated as

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

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

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

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

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.

2.3 Workload distribution

The values $I_{1,2}$ characterizing the cognitive performance of the subjects were compared at every moment. If the cognitive performance I_1 of the subject 1 exceeds the cognitive performance I_2 of the subject 2, the subject 1 gets the stimuli with high ambiguity, whereas the subject 2 gets the stimuli with low ambiguity.

2.4 Analysis of subject-subject interaction

The cognitive interaction between the subjects is performed via the Recurrence-based Measure of Dependence (RMD) proposed and described in details in Ref.[14] Using this approach one can either identify the coupling directions and the time lags between interacting systems or prove that they are independent. Let $I_1(i)$ and $I_2(i)$ be L and A brain response time series, respectively. Then, we calculate RMD as

$$\begin{aligned} RMD(\tau) &= \log_2\left(\frac{1}{N'}\sum_{i=1}^{N'} RMD_i(\tau)\right), \\ RMD_i(\tau) &= \frac{P(I_1(i), I_2(i+\tau)))}{P(I_1(i))\,P(I_2(i+\tau))}, \end{aligned}$$

where τ is a time lag, $P(I_k = I_k(i))$ is a probability for I_k to take the value $I_k(i)$, and $P(I_1(i), I_2(i)) = P(I_1 = I_1(i))\,P(I_2 = I_2(i))$ is a joint probability that $I_1 = I_1(i)$ at the same time, where $I_2 = I_2(i)$ and $N' = N - \tau$. The probabilities are determined using recurrence matrix calculations[15] as follows

$$\begin{aligned} P(I_k(i)) &= \frac{1}{N}\sum_{j=1}^{N} \mathbf{R}_k(i,j), \\ P(I_1(i), I_2(i)) &= \frac{1}{N}\sum_{j=1}^{N} \mathbf{JR}(i,j), \\ \mathbf{JR} &= \mathbf{R}_1(i,j)\,\mathbf{R}_2(i,j), \end{aligned}$$

where $\mathbf{R}_k(i,j)$ is a recurrence matrix of k-th participant and $\mathbf{JR}(i,j)$ is a joint recurrence matrix.

Next, we carry out the statistical test of the significance of the obtained $RMD(\tau)$ values using surrogate data of the observed time series. For this aim, we generate so-called twin surrogates, which are independent realizations of the entire system via the recurrence-based approach proposed in Ref.[16] The observed values of

$RMD(\tau)$ imply a statistically significant dependence of I_2 on I_1 if $RMD(\tau)$ exceeds 95 percentile (confidence interval) of the test $RMD(\tau)$ distribution calculated for I_1 surrogate time series. In the framework of this approach, we find that for $\tau > 0$ a non-zero RMD exceeding the confidence interval determines the dependence of I_2 on I_1, and the converse is true for $\tau < 0$. On the contrary, if RMD lies inside the confidence interval, the participants act independently.

3. RESULTS

The subject's cognitive performance has been measured based on the brain-response amplitude I (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 I, 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 τ. Following our work,[17] 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

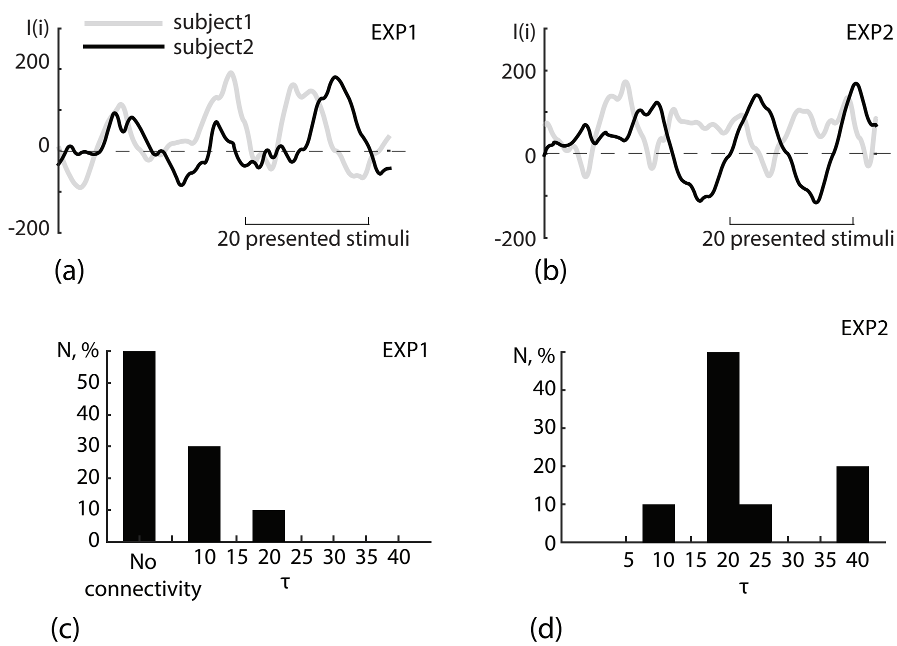

Figure 1. The subject's cognitive performance I during the second session of the experiment 1 (a) and experiment 2 (b); The RMD calculated for the cognitive performances for different timescales during the second session of the experiment 1 (c) and experiment 2 (d)

To analyze the features of the cognitive interaction resulting in the observed effect, we considered the coupling strength between the subjects based on the Recurrence-based Measure of Dependence (RMD) (see Methods).

RMD were calculated between the dependences of I over time for the second session of the experiment 1 and experiment 2. These dependences are shown in Fig. 1 for both subjects during the experiment1 (a) and experiment 2 (b). The Fig. 1 (c,d) illustrates the RMD values for the different time-scales. The highest RMD corresponds to the strongest interaction for the particular timescale. One can see, that for the experiment 1 the highest RMD is achieved for $\tau = 0$ manifesting the absence of the effective interaction between the subjects. In the experiment 2 the maximal RMD is observed for $\tau = 20$, corresponding to the 20 presented stimuli. Finally, it can be seen that τ corresponds to the period of the oscillations of the cognitive performance in the time (Fig. 1, b).

4. 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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