2021 5th Scientific School Dynamics of Complex Networks and their Applications (DCNA) | 978-1-6654-4283-1/21/$31.00 ©2021 IEEE | DOI: 10.1109/DCNA53427.2021.9587326

Analysis of behavioral characteristics during prolonged cognitive load

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***Abstract*—In the present work we studied human behavioral characteristics during prolonged cognitive activity. For this purpose we conducted experiment with interpretation of consistently presented ambiguous visual stimuli with different levels of ambiguity. As behavioral characteristic we chose the correctness of ambiguous stimuli interpretation and we showed, that number of errors changes significantly through the experiment.**

***Index Terms*—ambiguous visual stimuli, Necker cube, behavioral estimates, cognitive load**

I. Introduction

Mechanisms of brain adaptation or neuroplasticity is an important and promising research field. Neuroplasticity is the brain's inherent ability to respond to internal and external stimuli by reorganizing the neural network structure [1]. It is well known, that certain factors like developmental disorders and neurodegeneration through ageing greatly affect brain activity [2], [3]. Moreover, brain adaptation capabilities manifest themselves in response to more subtle changes too. For example, the human brain shows mental fatigue after prolonged cognitive load. This is due to the limited cognitive resources of the brain. Mental fatigue negatively affects person's attention and leads to a decrease in behavioral indicators [4]. However, studies show that the brain reserves cognitive resources to use them in the future [5], [6]. The brain makes optimal use of resources to recompense the effect of mental fatigue during prolonged cognitive activity.

The study of neurophysiological mechanisms of adaptation to cognitive load provides not only fundamental knowledge about the work of the human brain [7], but is also the basis for the development of both passive [8], [9] and active brain-computer interfaces [10]. The brain-computer interface (BCI) deciphers operator's brain activity and transforms its characteristic features into commands to control software and/or hardware in real-time. BCI was used as a basis to propose the concept of brain-to-brain interface (BBIs) — system featuring direct information transfer between the brains of interacting living beings. One of the possible applications of BBI is enhancement of performance in two-operator task — in this case interaction between operators can be used to share high mental load. The natural evolution of this approach is collaborative BCIs [11], [12], aimed to further enhance human performance by using multi-brain computing.

In this paper, we examined the behavioral characteristics of the subjects during long-term cognitive activity. We have shown that the distribution of events with incorrect interpretations of visual stimuli to the subjects is shifted to the beginning of the experimental session, which indicates the adaptation of the subjects to the cognitive task.

II. Methods

A. Participants and Experimental setup

The experiments involved 26 healthy volunteers aged 20 to 36 years with normal or adjusted-to-normal visual acuity. There were no subjects with history of neurological diseases and/or prescripted medications. The participants were asked to maintain a healthy lifestyle for 48 hours before the experiment, which included 8-hour night rest, limited consumption of alcohol and caffeine, moderate physical activity. The basic design of the experiment was explained to the volunteers? and they were informed about possible inconveniences. They were able to ask any related questions and received proper answers. All subjects signed informed written consent prior their participation. The experimental design was approved by the local Research Ethics Committee, and all experimental works were carried out in accordance with the Declaration of Helsinki.

Electroencephalogram (EEG) was acquired with NVX-52 amplifier (MKS, Zelenograd, Russia). To record EEG signals we used 31 standard Ag/AgCl electrodes, that were placed on the scalp according to the international "10-10" scheme. Two reference electrodes were placed on the left and right

AK is supported by the President program (MK-1760.2020.2) for behavioral data analysis. VG is supported by the Russian Foundation for Basic Research (19-32-60033) in conducting experiments

mastoids, and the ground electrode was placed on the forehead. During the experiment we monitored all electrode impedances and kept them below 15 kΩ to ensure high signal-to-noise ratio in acquired EEG signals. EEG data was recorded with sampling rate of 1 kHz and filtered with bandpass filter (cut-off frequencies 1 and 100 Hz) and 50 Hz notch filter.

B. Task

To study bistable visual perception and perceptual decision-making we chose the Necker cube [13]. An observer without perceptual deviations perceives this image as a 3D cube due to particular arrangement of the edges. Bistability lies in the perception of the Necker cube: it can be treated as left- or right-oriented. However, the degree of ambiguity can be controlled by changing the contrast of some edges. In our work we considered middle edges for this purpose — there are total six of them, three in the lower left part and three in the upper right part. We chose the contrast of the lower left edges as a control parameter $a = [0, 1]$ while the contrast of the upper right edges was $1 - a$. a was defined as $a = g/255$, where g is the brightness of the edges in terms of the 8-bit gray-scale palette. The boundary values $a = 1$ and $a = 0$ correspond to $g = 0$ (black) and $g = 255$ (white) pixels luminance of the edges. In this study we considered Necker cubes with eight values of $a = \{0.15, 0.25, 0.4, 0.45, 0.55, 0.6, 0.75, 0.85\}$ with first four treated as "left-oriented" (LO) and latter four as "right-oriented" (RO).

The Necker cubes were 14.2 cm in size and were drawn with gray lines on a white background in the center of a 24-inch monitor. The subjects seated in front of the monitor with eye-to-monitor distance of 70-80 cm and viewing angle of ~ 0.25 rad.

The subject's task was to interpret orientation of consequently presented Necker cubes and report their choice with two-button input device — right button press for RO Necker cube and left button press for LO Necker cube. During the experiment 400 Necker cubes evenly distributed over 8 different ambiguity levels were presented. The entire experiment lasted approximately 40 minutes for each participant.

During the experimental sessions, an experimental protocol was formed, which included the time of presentation of each visual stimulus, the subject's response time to the visual stimulus, the orientation of the visual stimulus, as well as the correctness of its interpretation.

C. Behavioral estimates

To analyze the behavioral characteristics, all Necker cubes demonstrated to the subjects during the experimental sessions were divided into two samples:

- Necker cubes with correctly interpreted orientation
- Necker cubes with incorrectly interpreted orientation

We used statistical analysis to compare these two samples. The statistical analysis was performed using SPSS statistics. The normality of the samples was checked using the Kolmogorov-Smirnov test. The main effect was evaluated using the Wilcoxon sign-rank test.

III. Results

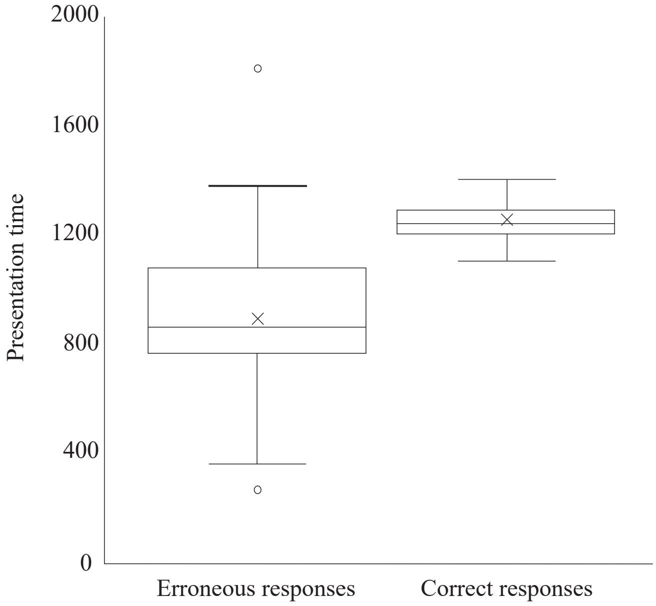

Fig. 1. Distribution of the presentation time over the experiment for correctly and incorrectly interpreted Necker cubes.

According to the Kolmogorov-Smirnov test, both samples followed a normal distribution ($p = 0.088$ and $p = 0.1$, respectively). The Wilcoxon sign-rank test showed significant differences between the median values of the visual stimulus presentation time for the samples under consideration ($p = 0.0002$).

Results of the statistical analysis are shown on Fig.1. According to visualization of median values, the Necker cubes with incorrectly interpreted orientation are distributed mainly in the initial phase of the experimental session, while the cases with correctly interpreted orientation are concentrated mostly in the latter half of the session.

Obtained results suggest decrease in number of errors from the start to the end of the experimental session. This implies some sort of adaptation to the cognitive task. The most obvious reason for these changes is the fact that the subject is getting familiar with the task which leads to increase in performance. However, this task can be treated as a prolonged cognitive load, which should inevitably lead to mental fatigue and, in its turn, decrease behavioral indicators. We speculate that observed increase in performance could be due to some intrinsic mechanism of brain adaptation to long-term cognitive load. Further studies in this field are planned, that will involve analysis of neurophysiological activity in a form of EEG.

IV. Conclusion

In this work we analyzed the behavioral characteristics of the subjects during the performance of a long-term cognitive task. It was revealed that the subjects make mistakes mainly at the beginning of the experimental session, which indicates that a person adapts to the assigned cognitive task. The obtained results provide grounds for further analysis of the identified mechanisms at the sensory level of brain neural activity. We suggest that knowledge of such mechanisms will open up new opportunities in development of BCIs, especially collaborative ones.

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