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A. A. Badarin, V. M. Antipov, Vadim V Grubov, S. A. Kurkin, "Changing functional connectivity during solving cognitive tasks: fNIRS study," Proc. SPIE 12194, Computational Biophysics and Nanobiophotonics, 121940L (29 April 2022); doi: 10.1117/12.2626381

SPIE.

Event: XXV Annual Conference Saratov Fall Meeting 2021; and IX Symposium on Optics and Biophotonics, 2021, Saratov, Russian Federation

Changing functional connectivity during solving cognitive tasks: fNIRS study

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ABSTRACT

In this paper, we present an analysis of the dynamics of functional connectivity of the cerebral cortical network using near-infrared spectroscopy during human solutions to simple cognitive tasks. A task-based on the Sternberg paradigm was chosen to provide a cognitive load. We identified statistically significant changes in the communication forces obtained on the basis of the analysis of oxyhemoglobin signals during the experiment. We found that in the course of the experiment, there is a restructuring of the functional network, which is accompanied by a decrease in the average connectivity strength between the cortical areas under study. We showed that there is a correlation between the subjective evaluation of fatigue degree and the characteristics of the identified functional neural network.

Keywords: Fatigue, fNIRS, functional network, visual analog scale, Sternberg paradigm

1. INTRODUCTION

Understanding of physical mechanisms and operation patterns of functional brain networks plays one of the key roles in understanding brain operation in general and is one of the most important and urgent problems of modern neuroscience.¹⁻⁸ In the context of this issue, of particular interest are the neural mechanisms by means of which functional brain networks are able to form and rearrange their topology for effective perception, processing, and decision-making under the condition of accumulated fatigue during the prolonged performance of routine tasks. Such interest is due not only to the fundamental importance of the issue, but also to its widely applied and social significance. In particular, disturbances in functional network adaptation mechanisms can lead to various neurological diseases or be a consequence of neurodegenerative diseases, such as Alzheimer's disease, dementia, and many others.⁹⁻¹¹ In turn, detection of such abnormalities plays an important role in the early diagnosis of these diseases.

Currently, scientific trends related to revealing the mechanisms of dynamic reorganization of the functional network of the brain when performing cognitive functions are being actively developed. The organization of the functional network of the brain is extremely dynamic, which allows it to form and reconstruct its topology for perception and processing of external and internal stimuli, adapting to changing conditions.¹²⁻¹⁵ Such adaptation and dynamism in the formation of connections between remote groups of neurons can explain the diverse functionality of the brain and provide a flexible mechanism that, in particular, allows maintaining high performance under prolonged cognitive load, as well as rapid switching between different types of tasks.¹⁶⁻¹⁹

The study of the temporal evolution of the functional brain network is unthinkable without the use of modern neuroimaging methods such as electroencephalogram(EEG)^{16,20}, functional near-infrared spectroscopy

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(fNIRS),^{21,22} magnetoencephalography (MEG).^{2,19} Application of fNIRS for this purpose appears to be one of the best options, since this technology combines a number of advantages, one of which, in particular, is the possibility to obtain information on the brain hemodynamic activity with a higher sampling frequency than that of magnetic resonance imaging.²³ These advantages of fNIRS technology are quite important for the most accurate and reliable determination of the dominant functional networks in the neuronal ensemble of the brain and can be used for brain-computer interfaces development.²⁴

This paper presents the results of an analysis of the evolution of the brain's functional network during long-term solution of simple cognitive tasks.

2. METHODS

2.1 Participants

We conducted an experimental study in which conditionally healthy volunteers with no history of neurological pathologies, aged 19 to 21, took part (14 people in total) from among the Innopolis University students to participate in this study. The volunteers were familiarized with the procedure for conducting the experiment in advance and were aware of the possible inconveniences associated with participating in the experiment. All volunteers had the opportunity to ask questions of interest and signed written informed consent in advance. The experimental study was approved by the local ethics committee and performed in accordance with the Declaration of Helsinki.

2.2 Experimental design

We performed a neurophysiological experiment aimed at analyzing brain activity under conditions of prolonged cognitive load. The proposed experimental design is based on the Sternberg paradigm. This task allows investigating processes of information processing in short-term memory and is widely used in various neurophysiological experiments.²⁵⁻²⁷ One of the advantages of this test is that the Sternberg task is well formalized, and its complexity can be easily adjusted using test parameters. Experimental design concludes several types of tests (MFI - Multidimensional Fatigue Inventory, NASA-TLX - The NASA Task Load Index, VAS - visual analog scale to evaluate fatigue) for a subjective evaluation of fatigue.²⁸⁻³⁰

The general experimental design is shown schematically in Fig. 1a. The experiment begins with the subject taking the MFI-20 test,²⁸ followed by the main part of the experiment, after which the subject takes the NASA-TLX test,²⁹ assessing the task-induced cognitive load, and the MFI-20 test a second time. Note that the main experimental part begins and ends with recording background hemodynamic activity for 60 seconds. The main part of the experiment consists of four identical blocks of tasks (1a), before and after each block of tasks the subject takes a visual analog scale to evaluate fatigue (VAS³⁰). Each block consists of 72 Sternberg tasks different difficult (see Fig. 1b).

The Sternberg task was implemented in the following form. Each task begins with a black screen on which a white cross is shown for 1.5-2.5 seconds, attracting the examinee's attention. Then a stimulus appears in the form of a set of 7 symbols, in which 2 to 7 symbols represent capital Cyrillic letters and the rest are "*". The set of letters is presented for 1.5-2.5 s, and the subject needs to remember the letters shown. A black screen is shown for 3-7 seconds, after which a lowercase letter is presented and the test person must answer whether it was present in the previously shown set or not. Note that showing a lowercase letter is necessary in order to make sure that the test person remembers the semantic meaning of the letter and not its visual image. The subject is asked to respond using two identical consoles pre-associated with the presence and absence of the letter in the set. Each block contains a total of 72 tasks, which are divided equally among six difficulties depending on the number of letters in the set, from 2 to 7 letters.

2.3 Fatigue and cognitive load inventory

The MFI-20 is a 20-item subjective multidimensional fatigue assessment scale that assesses fatigue on five scales: general fatigue, physical fatigue, reduced activity, reduced motivation and mental fatigue. In order to pass the test, the subject must give an answer from 1 to 5, where 1 is "Yes, that's true" and 5 is "No, that's not true" to

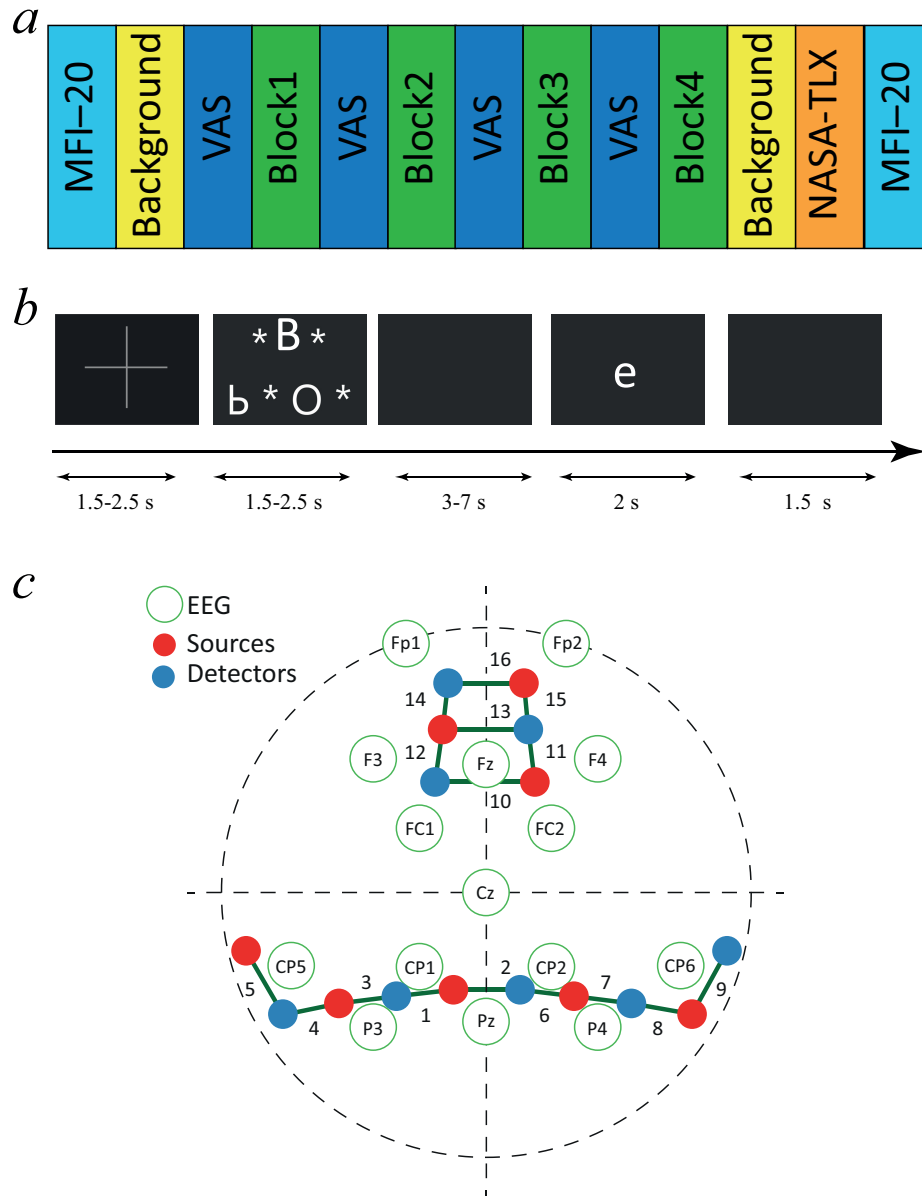


Figure 1. (a) Design of the neurophysiological experiment (here, MFI-20 - Multidimensional Fatigue Inventory, NASA-TLX - The NASA Task Load Index, VAS - visual analog scale to evaluate fatigue); (b) Scheme of one task from the block of the main part: cross for fixation of attention, presentation of a set of letters, pause, probe, pause for a response. (c) The EEG channels are given for a better understanding of the location of the fNIRS channels.

each of the statements presented. Note that the MFI-20 provides a comprehensive assessment of fatigue, with particular attention to the fatigue experienced by subjects.²⁸

NASA-TLX is a multidimensional scale designed to provide a subjective assessment of the test subject's fatigue during or immediately after a task. The test provides an assessment of the following factors: mental demand, physical demand, temporal demand, frustration, effort, and performance.²⁹

VAS is the fastest test in the presented design of the experiment, aimed at visual subjective assessment of fatigue. The essence of the test is as follows: the subject is shown a scale "Degree of Fatigue" with a slider and captions "Low" and "High" and he/she needs to move the slider with the mouse so that it reflects the current

degree of fatigue on the scale.³⁰

2.4 Recording and Processing of fNIRS

Brain activity was recorded using functional near-infrared spectroscopy (fNIRS). The fNIRS data reflect changes in the hemodynamics of certain brain tissue. To record hemodynamic response, we used NIRScout equipment manufactured by NIRx, Germany. This equipment uses radiation at two wavelengths ($\lambda_1 = 785$ nm and $\lambda_2 = 850$ nm). It should be noted that radiation in these ranges passes well through the connective tissues in the skull and is absorbed mainly by hemoglobin with oxygen and hemoglobin without oxygen in the blood, respectively. This effect makes it possible to monitor changes in oxy/deoxyhemoglobin concentrations and use them to assess brain tissue oxygenation.

NIRScout registers changes in radiation intensity with a sampling rate of 7.8125 Hz. The device has 8 sources and 8 detectors. When recording data, radiation from each of the sources passes through brain tissue at a depth of about 3 cm, is scattered and recorded by adjacent detectors. The trajectory along which the radiation travels from source to detector has a specific shape and depends on the distance between source and detector, which is chosen to be about 2-3 cm. Each source-detector pair forms one fNIRS channel. In the present experiment, sources and detectors were located in the frontal and parietal lobes and formed 16 fNIRS channels (see Fig. 1c).

Pre-processing of the experimental data from the neurophysiological experiment was performed in order to remove physiological artifacts such as Meyer waves (≈ 0.1 Hz), respiration (≈ 0.25 Hz), and heart rate (≈ 1 Hz). For this purpose, the experimental signals of the hemodynamic response of the brain were filtered in the range of 0.01-0.1 Hz, which allows excluding the influence of low-frequency physiological artifacts.³¹ The filtered data were used to calculate changes in the concentration of oxyhemoglobin and deoxyhemoglobin. In order to obtain information on the hemodynamic activity of the brain, the recorded signals are subjected to special processing - using a modified Bera-Lambert law,^{31,32} which makes it possible to obtain information on changes in the concentration of oxyhemoglobin, deoxyhemoglobin, total hemoglobin, as well as estimate oxygen saturation of brain tissue.

The obtained data on changes in oxyhemoglobin concentration was cut into epochs corresponding to each block of the experiment (see Fig.1a). Cross-correlation matrices were calculated for each epoch using Pearson's correlation coefficient.

2.5 Statistical Analysis

To identify connections and networks comprising the connectome that are associated with cognitive load and fatigue, we used Network-Based Statistic.³³

Changes of mean subjective evaluation of fatigue and the mean strength connectivity of the identified functional network during the experiment were assessed using repeated-measures analysis of variance (RM ANOVA). Post-hoc analysis was performed using the paired sample t-test with Holm correction for multiple comparisons.

The group-level correlation between the observed changes in the subjective evaluation of fatigue and the mean strength connectivity of the identified functional network was quantified using the repeated measures correlation (RM CORR) technique³⁴ in the Pingouin statistical package for Python.

3. RESULTS

We considered the dynamic of the subjective evaluation of fatigue during the experiment. We found that the subjective assessment of fatigue changes significantly during the experiment (see Fig. 2). Results of RM ANOVA for statistical evaluation of mean changes in VAS: F-value = 36.87, $p = 1.8 * 10^{-11}$. Moreover, post-hoc analysis showed significant changes between each pair of experimental blocks.

The dynamics of functional connections of the cerebral cortical network during long-term solution of simple cognitive tasks by a subject was analyzed. We revealed significant changes in the connectivity between oxyhemoglobin signals of fNIRS channels during the experiment by Network-Based Statistic. In particular, changes in the strength of connectivity between and within the parietal and frontal lobes of the brain were found (see Fig. 3a). We observe that during the experiment, there is a restructuring of the functional network, which

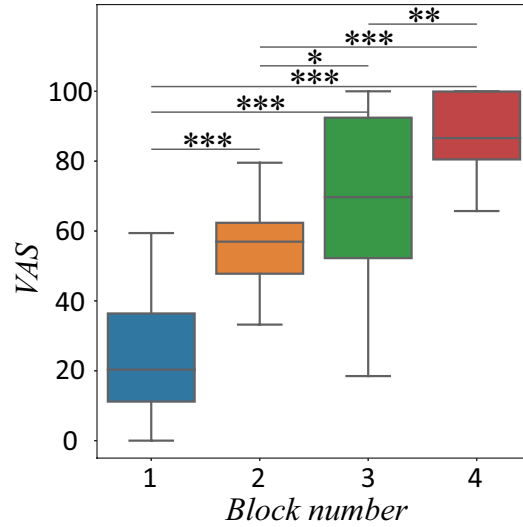


Figure 2. Distribution of the subjective evaluation of fatigue (VAS) during the experiment. Significant changes in the post-hoc analysis are marked with * : * - $p < 0.05$; ** - $p < 0.01$, *** - $p < 0.001$; Results of RM ANOVA for statistical evaluation of mean changes in VAS: F-value = 36.87, $p = 1.8 \times 10^{-11}$.

is accompanied by a decrease in the mean strength of connectivity (see Fig. 3b). Results of RM ANOVA for statistical evaluation of mean changes in connectivity: F-value = 9.36, $p = 8.6 \times 10^{-6}$. Post-hoc analysis showed significant changes between 1-3 and 1-4 pairs of experimental blocks.

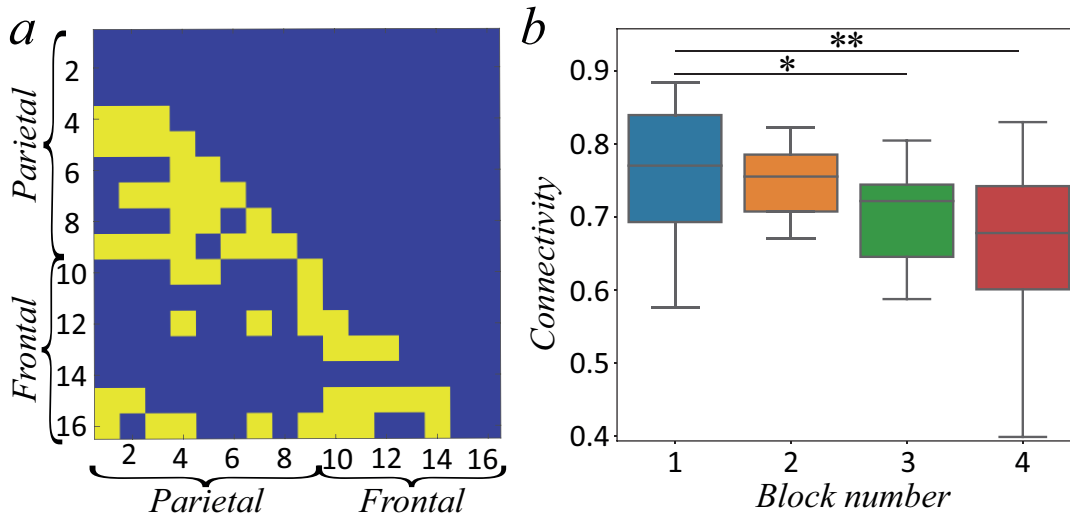


Figure 3. (a) Map of significant changes in connectivity between fNIRS channels obtained using Network-Based Statistic. (b) Distribution of the mean strength connectivity of the identified functional network during the experiment. Significant changes in the post-hoc analysis are marked with * : * - $p < 0.05$; ** - $p < 0.01$; Results of RM ANOVA for statistical evaluation of mean changes in connectivity: F-value = 9.36, $p = 8.6 \times 10^{-6}$.

We analyzed correlations between the subjective psychophysiological state of the subject (VAS, fig. 2) and the characteristic reflecting the neural activity of the cerebral cortical network(connectivity, fig. 3b). Results of RM CORR between the observed changes in the subjective evaluation of fatigue and the mean strength connectivity of the identified functional network: $r = -0.545107$, confidence interval $[-0.73, -0.29]$; p -value= 0.000157 ; power= 0.974097 .

ACKNOWLEDGMENTS

The experimental work was supported by the Russian Science Foundation (grant 19-72-10121). The analysis of functional neural networks was supported by the Russian Foundation for Basic Research (grant 19-29-14101).

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