PROCEEDINGS OF SPIE

SPIEDigitalLibrary.org/conference-proceedings-of-spie

Network structure of children's brain activity during cognitive load

Hramov, Alexander, Grubov, Vadim, Frolov, Nikita, Pitsik, Elena, Khramova, Marina

Alexander E. Hramov, Vadim V. Grubov, Nikita S. Frolov, Elena N. Pitsik, Marina V. Khramova, "Network structure of children's brain activity during cognitive load," Proc. SPIE 11459, Saratov Fall Meeting 2019: Computations and Data Analysis: from Nanoscale Tools to Brain Functions, 1145909 (9 April 2020); doi: 10.1117/12.2564343

Event: Saratov Fall Meeting 2019: VII International Symposium on Optics and Biophotonics, 2019, Saratov, Russian Federation

Network structure of children's brain activity during cognitive load

Alexander E. Hramov[a], Vadim V. Grubov[a], Nikita S. Frolov[a], Elena N. Pitsik[a], Marina V. Khramova[b]

[a]Neuroscience and Cognitive Technology Laboratory, Center for Technologies in Robotics and Mechatronics Components, Innopolis University, 420500, Innopolis, The Republic of Tatarstan, Russia

[b]Saratov State University, 410012, Saratov, Russia

ABSTRACT

We have analyzed the neuronal interactions in the children's brain cortex associated with the cognitive activity during simple cognitive task (Schulte table) evaluation in two distinct frequency bands – alpha (8–13 Hz) and beta (15–30 Hz) ranges using linear Pearsons correlation-based connectivity analysis. We observed the task-related suppression of the alpha-band connectivity in the frontal, temporal and central brain areas, while in the parietal and occipital brain regions connectivity exhibits increase. We also demonstrated significant task-related increase of functional connectivity in the beta frequency band all over the distributed cortical network.

Keywords: Artificial neural network, machine learning, nonlinear dynamics, synchronization, functional connectivity

1. INTRODUCTION

The problem of the development and implementation of high technologies in the educational process, allowing to optimize educational activities and increase the efficiency of perception of new information, is an important modern task requiring interdisciplinary approaches.[1] In this context, the most intriguing problems are devoted to the analysis of the psychophysiological state of a person during educational activities and solving cognitive tasks. For example, special attention is paid to studying the brain's structure and its cognitive functions to improve the quality of learning.[2] At the moment, the symbiosis of these scientific fields presents great opportunities for optimizing the educational process based on the achievements of cognitive neuroscience.[3,4] Notable success has been achieved in the preschool education.[5] In Ref.[6] the authors showed that, based on the knowledge of the physiological mechanisms of the development of dyslexia and the syndrome of distracted attention in children, it became possible to correct educational activities to suppress these pathologies. There is also possibility to implement the robotics systems controlling by neuronal activity in educational process.[7] In our recent work[8] we have shown that a number of cognitive and psychological characteristics of a person can be evaluated using EEG data during simple tests for the development of attention and memory (Schulte table). Thus, we can conclude that, understanding the features of cognitive activity of students during the educational process, it is possible to significantly increase the effectiveness of training and the quality of assimilation of new information. The key to understanding students' cognitive activity is registering brain activity during the assimilation of new material and developing advanced mathematical methods for analyzing the recorded data obtained during training and/or passing tests.

In the course of the mentioned problem the most suitable neuroimaging technique is electroencephalography (EEG), primarily due to good frequency resolution, ease of signal acquisition and low cost compared to methods such as functional magnetic resonance imaging (fMRI), positron emission tomography (PET) or magnetoencephalography (MEG). Usually, correlations between neuronal activity and psychophysiological state are considered in terms of segregation of brain regions and quantifying their behavior using standard methods of

Further author information: (Send correspondence to N.S. Frolov)
N.S. Frolov: E-mail: n.frolov@innopolis.ru

Saratov Fall Meeting 2019: Computations and Data Analysis: from Nanoscale Tools to Brain Functions, edited by Dmitry E. Postnov, Proc. of SPIE Vol. 11459, 1145909 · © 2020 SPIE
CCC code: 1605-7422/20/$21 · doi: 10.1117/12.2564343

time-frequency analysis,[8–10] event-related potentials analysis[11–13] as well as artificial intelligence and machine learning.[14, 15]

However, in accordance with modern concepts, the normal functioning of the brain, especially various aspects of its cognitive activity, are associated with complex neural interactions that occur in the spatially distributed cortical network of the brain.[16–19] The integration process seeks to use the cerebral cortex areas that are functionally distant and distant from each other in space in order to solve a complex task that requires concentration of visual attention, involvement of short-term memory, and spatial thinking. Such tasks include the assimilation of new information, the implementation of logical, arithmetic and lexical operations. At the same time, the efficiency of the brain during the long-term solution of such cognitive tasks, as we have shown, cannot be maintained at the same level.[20, 21] The weakening of neural interactions and the reconfiguration of the network of functional connections between brain regions are objective factors that can reflect cognitive fatigue and a decrease in the perception of new information.[22]

This paper aims at the revealing features of functional connectivity in children's brain network while performing Schulte table test. Particularly, we consider workload network patterns in alpha (8-13 Hz) and beta (15-30 Hz) frequency bands and analyze inter-areal brain communication under the mental task accomplishment.

2. METHODS

2.1 Participants

Participants were recruited among the children of the Innopolis University employees (5 healthy subjects, aged 7–10, right-handed, never participated in this or similar experiments before and having no history of medical brain conditions). All the participants as well as their parents were pre-informed about the goals and design of the experiment. Experimental studies were performed in accordance with the Declaration of Helsinki and approved by the local research Ethics Committee of Innopolis University.

2.2 Data acquisition

EEG signals were recorded using non-invasive EEG system actiCHamp (Brain Products GmbH, Germany) presented in Fig. 1a. Electrocardiogram (ECG) and electro-oculogram (EOG) were also recorded for further removal of cardiac and eye-movement artifacts. All recorded signals were amplified and digitized at the sampling rate of 1000 Hz. To capture neuronal processes in spatially extended brain network we used 31 EEG Ag/AgCl electrodes according to the international "10-10" system proposed by the American Electroencephalographic Society (Fig. 1b).

2.3 Experimental procedure

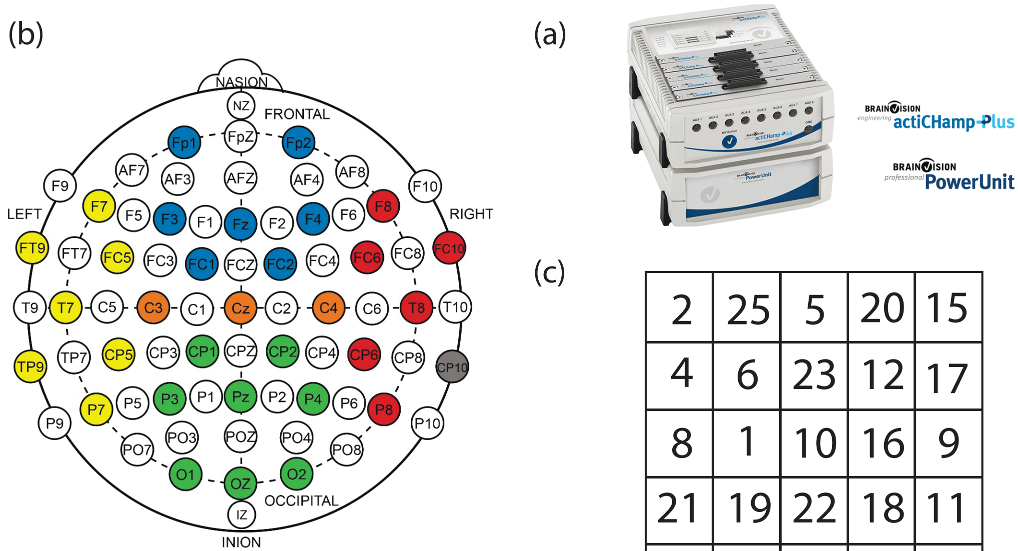
The experimental session started with a 5-min recording of the background brain activity, during which the participating children were instructed to relax and listen to classical music. Then, during the active phase of the experiment each participant was instructed to evaluate mental tasks (Schulte table test). Schulte table, representing in a classical form a 5x5 grid with random distribution of numbers over the cells, is used to measure cognitive performance indexes based on the efficiency of its evaluation (Fig. 1c).[8] First, participant solved Schulte table adapted for children in a playful form. After understanding the paradigm of the task, they were asked to solve two classical Schulte tables with a short resting period of about 15–20 seconds. Each table performance took at least 42 seconds and 51 seconds on average.

2.4 Data preprocessing

The following preprocessing steps were carried out to prepare raw EEG recordings for further analysis.

First, raw EEG recordings were down-sampled to 250 Hz.

Second, cardiac and eye-movement artifacts were removed using recorded ECG and EOG signals via artifact removal method based on the independent component analysis (ICA).[23] A Notch filter around 50 Hz was applied to EEG and EMG data to exclude power line effects.



(c)

2	25	5	20	15
4	6	23	12	17
8	1	10	16	9
21	19	22	18	11
14	24	3	13	7

Figure 1. (a) Electroencephalograph actiCHamp (Brain products GmbH, Germany) used for high-resolution children's brain electrical activity recording. (b) International 10-10 EEG system. Highlighted sensors were used in the study and colored in accordance with clustering. (c) Typical example of Schulte table.

Finally, we applied a 5th-order Butterworth band-pass filter in the 8–13 Hz and 15–30 Hz frequency ranges to the entire multichannel EEG signals in order to extract α- and β-band neuronal oscillations. Finally, the bandpass filtered time series were split into 3 segments, each lasting 40 seconds – one segment baseline activity preceding mental tasks accomplishment and two segments of brain activity corresponding to Schulte table evaluation.

2.5 Functional connectivity analysis

First, we composed 31 EEG signals into 6 clusters in accordance with their location: frontal F (Fp1, Fp2, F3, Fz, F4, Fc1, Fc2), left temporal LT (F7, Ft9, Fc5, T7), right temporal RT (F8, Fc10, Fc6, T8), central C (C1, Cz, C2, Cp1, Cpz, Cp2), parietal P (P1, Pz, P2), occipital O (O1, Oz, O2) (see Fig. 1b).

Pairwise linear connectivity analysis was performed using calculation of Pearson's correlation coefficient ρ. Consider a pair of signals $X^{b,t}(t)$ and $Y^{b,t}(t)$ in background (superscript b) and task-related (superscript t) activity. We provided windowed connectivity analysis with window width $w = 2$ s (500 data points) and overlapping $\delta w = 1$ s (250 data points) following the equation:

$$\rho^{b,t}_{XY}(t_i) = \frac{\mathrm{Cov}(X^{b,t'}_i, Y^{b,t'}_i)}{\sigma X^{b,t'}_i \sigma Y^{b,t'}_i}, \tag{1}$$

where $X^{b,t'}_i$ and $Y^{b,t'}_i$ are mean-averaged samples of $X^{b,t}(t)$ and $Y^{b,t}(t)$ within i-th window with standard deviation $\sigma X^{b,t'}_i$ and $\sigma Y^{b,t'}_i$ normalized to 1. To reveal significant between-subject changes of functional connectivity associated with mental task evaluation we applied pairwise t-test for related samples to ρ^t_{XY} and ρ^b_{XY}. Multiple comparison problem (MCP) due to the simultaneous pairwise comparison of 930 links was corrected via permutation test following Ref.[24]

3. RESULTS

Fig. 2 illustrates the coupling matrices of brain functional connectivity in the alpha band obtained during windowed linear correlation analysis. Here, each cell contains weight of the link between corresponding EEG

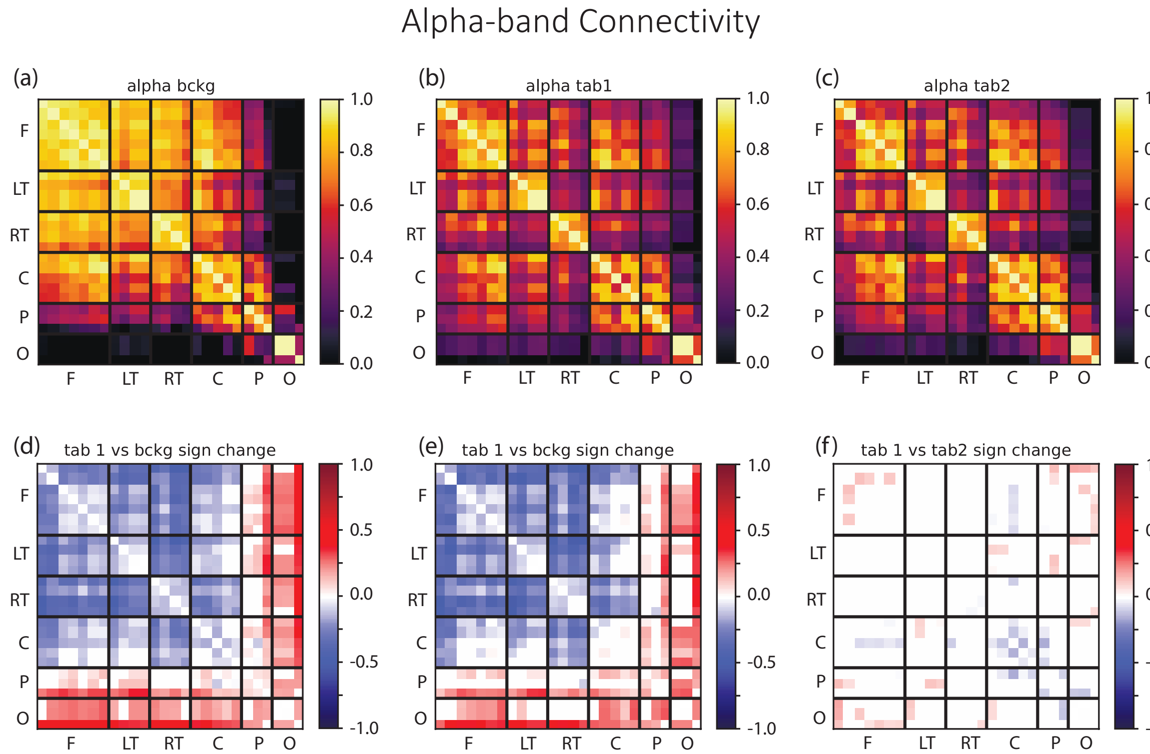


Figure 2. Coupling matrices of brain functional connectivity in the alpha band containing mean values $\overline{\rho_{XY}^{bt}}$ for background activity (a) and brain activity associated with Shulte tables evaluation (b,c). Significant task-related changes of functional connectivity matrices (d,e) and differences between the tasks (f).

sensors introduced as a mean value of Pearson's correlation coefficient $\overline{\rho_{XY}^{bt}}$. First of all, one can clearly see that coupling matrices in background (a) and task-related activity (b,c) are completely different, while task-related matrices share the same pattern. Statistical t-test for independent samples with cluster-based MCP correction based on random partitions reveals task-related changes of the brain functional connectivity consist in reduction of correlation between the sensors of frontal, temporal and central regions, whereas the correlation between the occipito-parietal area with the other regions increases (d,e). At the same time, brain functional connectivity matrices obtained during two consequent evaluations of the Schulte tables are almost identical with rare significant differences (f).

Fig. 3 demonstrates the similar effects of task-related changes in brain functional connectivity structure, but in the beta range. It is also seen, that neuronal interactions in the beta band happen in the same way during task-related activity (b,c), which is different from the resting state (a). Having analyzed the statistical differences, we observed that neuronal interactions between EEG sensors exhibit increase of the linear correlation coefficient in almost every pair of sensors. One can see, from (d,e) that interaction between the right temporal (RT) area and the other brain regions demonstrates the most pronounced increase of correlation.

Taken together, the results of the functional connectivity of children's brain during mental task accomplishment show the suppression of the interaction in the alpha band, except for the link between occipito-parietal region and frontal and central regions. On the contrary, beta-band connectivity increases with dominating role of right temporal zone. These results are in line with the knowledge about the pathways of the visual sensory information within the cortical brain network through the synchrony of alpha-oscillations in the occipito-parietal zone and frontal area. At the same time, activation of the beta-band neuronal interactions in the right temporal area indicates the brain region involved in visual sensory information processing.

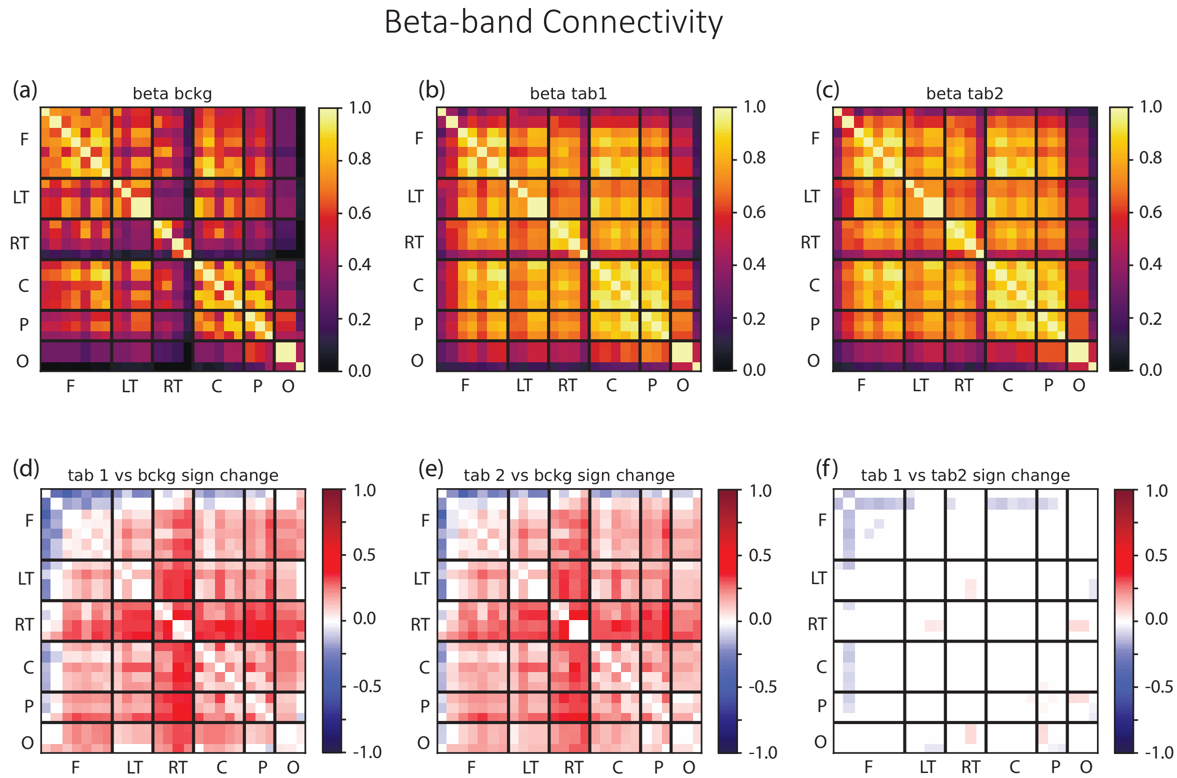


Figure 3. Coupling matrices of brain functional connectivity in the beta band containing mean values $\overline{\rho_{XY}^{bt}}$ for background activity (a) and brain activity associated with Shulte tables evaluation (b,c). Significant task-related changes of functional connectivity matrices (d,e) and differences between the tasks (f).

4. CONCLUSION

We have analyzed the neuronal interactions in the children's brain cortex associated with the cognitive activity during Schulte table evaluation in two distinct frequency bands – alpha (8-13 Hz) and beta (15-30 Hz) – using linear Pearsons correlation-based connectivity analysis. We observed the task-related suppression of the alpha-band connectivity in the frontal (F), temporal (LT and RT) and central (C) areas, while in the parietal (P) and occipital (O) regions connectivity exhibits increase. We also demonstrated significant task-related increase of functional connectivity in the beta band all over the distributed cortical network.

5. ACKNOWLEDGMENTS

This work has been supported by the Russian Foundation for Basic Research (Grant 19-29-14101).

REFERENCES

[1] Truong, H. M., "Integrating learning styles and adaptive e-learning system: Current developments, problems and opportunities," *Computers in human behavior* **55**, 1185–1193 (2016).

[2] Goswami, U., "Neuroscience and education: from research to practice?," *Nature reviews neuroscience* **7**(5), 406 (2006).

[3] Meltzer, L., [*Executive function in education: From theory to practice*], Guilford Publications (2018).

[4] Aleksandrova, N. A., Chernyaeva, T. N., Khramova, M. V., and Hramov, A. E., "The implementation of the innovation platform" educational potential of hardware-software complexes based on the study and interpretation of brain activity patterns"," in [*2018 IEEE International Conference" Quality Management, Transport and Information Security, Information Technologies"(IT&QM&IS)*], 533–535, IEEE (2018).

[5] Dubinsky, J. M., "Neuroscience education for prekindergarten–12 teachers," *Journal of Neuroscience* **30**(24), 8057–8060 (2010).

[6] Goswami, U., "Mind, brain, and literacy: Biomarkers as usable knowledge for education," *Mind, Brain, and Education* **3**(3), 176–184 (2009).

[7] Aleksandrova, N. A., Hramov, A. E., and Khramova, M. V., "Designing, implementation and use of robotic devices in the social sectors in foreign studies," in [*2018 IEEE International Conference" Quality Management, Transport and Information Security, Information Technologies"(IT&QM&IS)*], 536–541, IEEE (2018).

[8] Maksimenko, V. A., Runnova, A. E., Zhuravlev, M. O., Protasov, P., Kulanin, R., Khramova, M. V., Pisarchik, A. N., and Hramov, A. E., "Human personality reflects spatio-temporal and time-frequency eeg structure," *PloS one* **13**(9), e0197642 (2018).

[9] Maksimenko, V. A., Hramov, A. E., Grubov, V. V., Nedaivozov, V. O., Makarov, V. V., and Pisarchik, A. N., "Nonlinear effect of biological feedback on brain attentional state," *Nonlinear Dynamics* **95**(3), 1923–1939 (2019).

[10] Pavlov, A. N., Hramov, A. E., Koronovskii, A. A., Sitnikova, E. Y., Makarov, V. A., and Ovchinnikov, A. A., "Wavelet analysis in neurodynamics," *Physics-Uspekhi* **55**(9), 845 (2012).

[11] Duvinage, M., Castermans, T., Petieau, M., Hoellinger, T., Cheron, G., and Dutoit, T., "Performance of the emotiv epoc headset for p300-based applications," *Biomedical engineering online* **12**(1), 56 (2013).

[12] Badcock, N. A., Preece, K. A., de Wit, B., Glenn, K., Fieder, N., Thie, J., and McArthur, G., "Validation of the emotiv epoc eeg system for research quality auditory event-related potentials in children," *PeerJ* **3**, e907 (2015).

[13] McCarthy, G. and Donchin, E., "A metric for thought: a comparison of p300 latency and reaction time," *Science* **211**(4477), 77–80 (1981).

[14] Ramirez, R. and Vamvakousis, Z., "Detecting emotion from eeg signals using the emotive epoc device," in [*International Conference on Brain Informatics*], 175–184, Springer (2012).

[15] Frolov, N., Maksimenko, V., Lüttjohann, A., Koronovskii, A., and Hramov, A., "Feed-forward artificial neural network provides data-driven inference of functional connectivity," *Chaos: An Interdisciplinary Journal of Nonlinear Science* **29**(9), 091101 (2019).

[16] Medaglia, J. D., Lynall, M.-E., and Bassett, D. S., "Cognitive network neuroscience," *Journal of cognitive neuroscience* **27**(8), 1471–1491 (2015).

[17] Makarov, V. V., Zhuravlev, M. O., Runnova, A. E., Protasov, P., Maksimenko, V. A., Frolov, N. S., Pisarchik, A. N., and Hramov, A. E., "Betweenness centrality in multiplex brain network during mental task evaluation," *Physical Review E* **98**(6), 062413 (2018).

[18] Frolov, N. S., Maksimenko, V. A., Khramova, M. V., Pisarchik, A. N., and Hramov, A. E., "Dynamics of functional connectivity in multilayer cortical brain network during sensory information processing," *The European Physical Journal Special Topics* **228**(11), 2381–2389 (2019).

[19] Maksimenko, V. A., Frolov, N. S., Hramov, A. E., Runnova, A. E., Grubov, V. V., Kurths, J., and Pisarchik, A. N., "Neural interactions in a spatially-distributed cortical network during perceptual decision-making," *Frontiers in behavioral neuroscience* **13**, 220 (2019).

[20] Maksimenko, V. A., Runnova, A. E., Zhuravlev, M. O., Makarov, V. V., Nedayvozov, V., Grubov, V. V., Pchelintceva, S. V., Hramov, A. E., and Pisarchik, A. N., "Visual perception affected by motivation and alertness controlled by a noninvasive brain-computer interface," *PloS one* **12**(12), e0188700 (2017).

[21] Maksimenko, V. A., Hramov, A. E., Frolov, N. S., Lüttjohann, A., Nedaivozov, V. O., Grubov, V. V., Runnova, A. E., Makarov, V. V., Kurths, J., and Pisarchik, A. N., "Increasing human performance by sharing cognitive load using brain-to-brain interface," *Frontiers in neuroscience* **12** (2018).

[22] Betzel, R. F., Satterthwaite, T. D., Gold, J. I., and Bassett, D. S., "Positive affect, surprise, and fatigue are correlates of network flexibility," *Scientific Reports* **7**(1), 520 (2017).

[23] Hyvärinen, A. and Oja, E., "Independent component analysis: algorithms and applications," *Neural networks* **13**(4-5), 411–430 (2000).

[24] Mamashli, F., Hämäläinen, M., Ahveninen, J., Kenet, T., and Khan, S., "Permutation statistics for connectivity analysis between regions of interest in eeg and meg data," *Scientific reports* **9**(1), 7942 (2019).