

# Features of the Functional Brain Network under Combined Cognitive Load

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**Abstract**—In the current study, we reconstructed functional brain networks based on EEG (electroencephalography) of children aged 8 to 14 years when performing cognitive tasks related to learning processes, and analyzed network features associated with performing combined tasks, compared with simpler tasks aimed at working a specific cognitive function (visual search, mental arithmetic or working memory). To calculate connectivity, we chose the method of calculating the Imaginary Part of Coherence (ICOH) in the main EEG rhythms (theta, alpha and beta oscillations). The results obtained can be useful in the search for biomarkers to assess the effectiveness of complex cognitive tasks.

**Index Terms**—EEG, cognitive task, functional analysis, functional brain network, Network-Based Statistic

## I. INTRODUCTION

In our day, the study of functional brain networks, which are a set of connections between different areas of the brain, reconstructed based on time series of electrical activity of neurons, is a key area. These networks are described by statistical correlations between the dynamics of activity in different brain regions. This area has become especially relevant in the context of the study of cognitive processes, as it allows for a deeper understanding of the mechanisms of functioning of higher mental functions [1], [2]. Special attention should be paid to the analysis of children's brain activity, which is not only of fundamental scientific importance, but also has significant applied potential. The results of such studies can be used to optimize educational processes, taking into account the psychophysiological characteristics of students [3], [4], as well as to diagnose cognitive impairments and assess the degree of development of mental abilities [5]–[7].

One of the promising methods of functional analysis of brain activity is the application of graph theory. This approach makes it possible to reconstruct functional brain networks based on neurophysiological data, where graph nodes correspond to individual brain regions or electroencephalogram (EEG) leads, and graph edges reflect the degree of synchronization of activity between these nodes [8].

This work is a continuation of our study of the neurobiological foundations of cognitive functions in children [9]. The main purpose of this stage of the study is to analyze the functional brain networks of children aged 8-14 years when

performing a combined cognitive load associated with learning processes.

## II. METHODS

The experiment involved 94 participants aged 8 to 14 years (41 girls, 53 boys, average age  $11.57 \pm 1.97$  years), and its implementation was approved by the Ethics Committee of the Immanuel Kant Baltic Federal University (Protocol No. 32 dated 07/04/2022).

The experimental paradigm included four types of tasks associated with learning processes. The "Visual Search" task required the subjects to find the target elements in a matrix of numbers, where the difficulty varied depending on the size of the matrix. The "Mental Arithmetic" task assessed the computational abilities of the subjects, asking them to determine the truth of arithmetic expressions and press the appropriate button. The difficulty of the task varied depending on the amount of the deduction. The "Working Memory" task, based on the Sternberg paradigm, involved presenting a random set of two-digit numbers and the characters "Y", followed by a request for the presence of the presented number in the previously shown set. The difficulty of the task also varied depending on the number of numbers in the set. The task type "Combined Functions" were a modification of the Schulte tables and included a combined cognitive load: the subject had to memorize a pair of numbers, subtract the second from the first and find the result of the subtraction in a matrix of numbers (one trial contained several repetitions of the "subtraction - search" cycles).

The experiment consisted of three equal blocks, each of which randomly presented a series of cognitive tests of various types. Each block started with recording background activity at rest for 1 minute and ended with a 2-minute break. The total duration of the experiment was about 45 minutes, excluding the time of electrode installation and briefing, which took about 65 minutes in total. Participants were advised to avoid conversations and minimize non-task-related physical activity. During the breaks, the subjects could rest, but they were not allowed to get up from the table. If the participant refused to continue the experiment, he could complete it ahead of schedule, but the data from such sessions were not included in the analysis due to the unequal number of completed tasks. The

detailed design of the experiment is described in the previously published work (V. Grubov, 2024 [3]).

We recorded the electroencephalogram (EEG) using 64 active electrodes of an encephalograph with a sampling frequency of 500 Hz, in accordance with the standard "10-10" scheme [10]. Data preprocessing included linear filtering in the frequency range from 0.1 to 40 Hz, as well as the removal of artifacts using the method of independent components (ICA) [11].

Segmentation of EEG recordings was performed by highlighting significant fragments for each task cycle. For each task, a solution period was selected, starting from the moment the task was presented, and the same period of time was counted from the background activity preceding the task. Thus, two phases were performed for each cycle: the first was an EEG fragment during the task, and the second was an EEG fragment at rest. This approach allowed for a comparative analysis of brain activity under conditions of cognitive load and rest. Then we averaged the connectivity values for the ten zones to which each of the leads belongs: Frontal, Temporal, Central, Parietal, and Occipital zones for the left and right hemispheres, respectively.

To assess the interconnectedness of neural activity, we calculated the imaginary coherence coefficient (ICOH), which is considered more resistant to the phenomenon of field spread (a phenomenon in which electrical signals from a single neural source are transmitted through brain tissue to several electrodes on the scalp) compared to the traditional method of determining consistency analysis, since it ignores synchronization with zero phase delay (with a high probability related to the same source) and, thus, can display more reliable interactions of neural structures. [12]. The connectivity was calculated in the main frequency ranges: theta (4-8 Hz), alpha (8-13 Hz) and beta (13-32 Hz) [13]. We averaged the indicators for each type of task, the condition of each subject, and each frequency range.

Based on connection matrices using the Network-Based Statistics (NBS) [14] statistical method with a threshold value of  $p = 0.01$ , we determined functional networks associated with performing certain types of tasks in different frequency ranges. Next, we compared the networks corresponding to the "Combined Functions" task type with the other three types in order to identify those edges (and therefore connections) that are present only when solving combined tasks.

### III. RESULTS

We found synchronizations between individual brain regions that appear with combined cognitive load and have no statistical significance in other types of tasks (see Fig. 1):

- 1) Theta-band: "Temporal Left" – "Temporal Right", "Central Left – Occipital Left", "Central Right – Occipital Right";
- 2) Alpha-band: "Frontal Right" – "Central Left", "Frontal Right" – "Parietal Left", "Frontal Right" – "Central Right", "Frontal Right" – "Occipital Right"; "Central

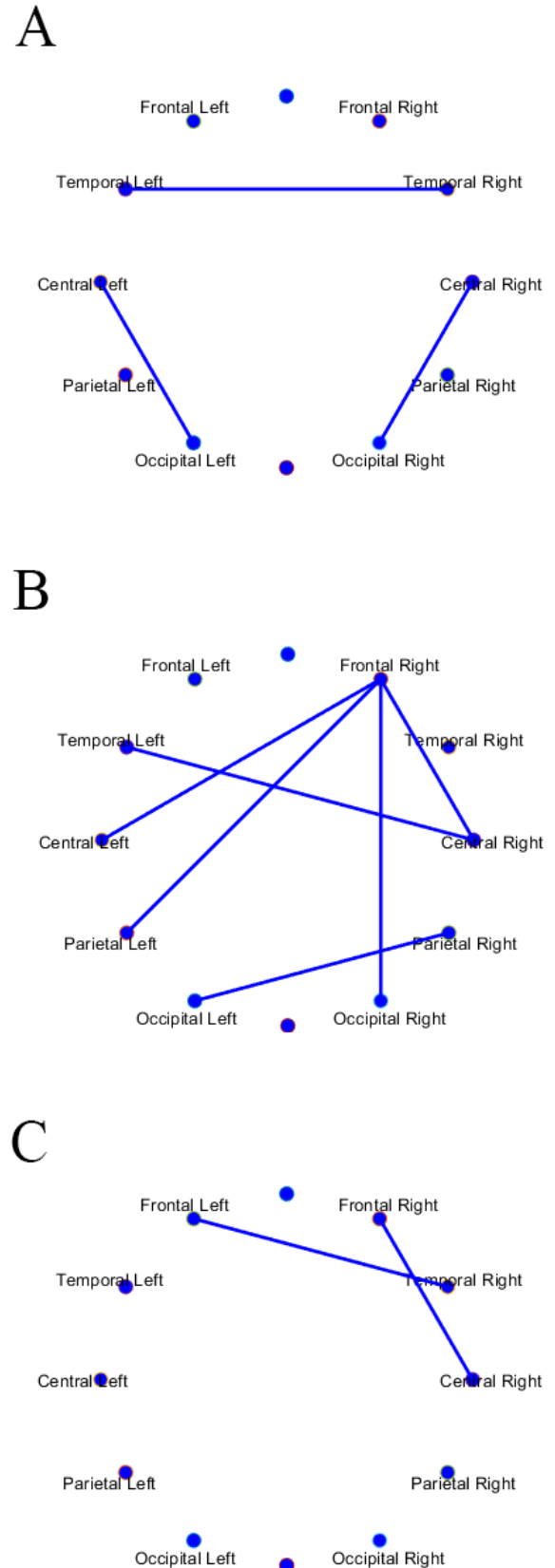


Fig. 1. The schemes of the relationships that appear when solving problems such as "Combine functions" in comparison with other types of tasks for theta (A), alpha (B) and beta (C) oscillations.

Right” – ”Temporal Left”, ”Occipital Left” – ”Parietal Right”;

- 3) Beta-band: ”Frontal Left” – ”Temporal Left”, ”Frontal Right” – ”Central Right”.

In addition, among the limitations of this work, it is worth noting that the work describes only those functional relationships that appear when combining these cognitive functions in comparison with solving tasks more focused on a specific cognitive function: those relationships that do not statistically significantly manifest themselves in the sample for tasks such as ”Combined Functions” are not indicated. but they are present when solving experimental problems of other types. Thus, functional connections with the combined use of cognitive functions not only appear, but also disappear, and the functional network of the brain can become much more fundamental.

The appearance of these functional connections exclusively in the ”Combining Functions” type of tasks may indicate the formation of an integrated cognitive network dynamically created to coordinate the work of usually more autonomous systems: working memory, executive control, mental computing, and visual search. This may be a manifestation of the brain’s neuroplasticity and adaptability to solving complex tasks in real time [15], [16].

#### IV. CONCLUSION

The results obtained may show which functional connections between brain regions are formed under combined cognitive load. Of further interest is the study of the characteristics of such a network, as well as the search for correlations between them and task performance data (for example, reaction time and the number of correct answers).

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