Features of Functional Brain Connectivity in Children During Working Memory Tasks

Oleg Piljugin
Immanuel Kant Baltic Federal University
Kaliningrad, Russia
Plekhanov Russian University of Economics
Moscow, Russia
ovplgn@gmail.com

Vladimir Antipov
Research institute of Applied Artificial Intelligence and Digital Solutions
Plekhanov Russian University of Economics
Moscow, Russia
vantipovm@gmail.com

Artem Badarin
Research institute of Applied Artificial Intelligence and Digital Solutions
Plekhanov Russian University of Economics
Moscow, Russia
Badarin.a.a@mail.ru

2026 10th Scientific School Dynamics of Complex Networks and their Applications (DCNA) | 979-8-3195-2599-4/26/$31.00 ©2026 IEEE | DOI: 10.1109/DCNA72004.2026.11733382

***Abstract*—In the current study, we investigated frequency-specific features of functional brain networks in children aged 8–14 years during working memory task performance using EEG data. We found that the mean weighted node degree was highest in the theta band, whereas faster task performance was associated with a higher mean weighted node degree in the alpha band. These findings suggest that, although theta-band networks exhibited the strongest overall functional connectivity, individual differences in behavioral performance were specifically associated with alpha-band network connectivity.**

***Index Terms*—EEG, working memory, functional brain network, coherence**

I. Introduction

In neuroscience, functional connectivity of the brain refers to the coherence of neuronal activity, determined through statistical analysis. The study of neural interactions during cognitive development is of interest for understanding the neurophysiological mechanisms underlying learning and intellectual development in children [1]. Working memory is understood as a cognitive function that allows you to actively store and use a limited set of information to solve a current task and plays a key role in learning-related processes, so its development has a significant impact on the effectiveness of the educational process [2], [3].

Functional networks (sets of brain regions with similar neural activity) are reconstructed using data obtained using brain activity recording techniques: the most commonly used are electroencephalography (EEG), magnetoencephalography (MEG), functional near-infrared spectroscopy (fNIRS), and functional magnetic resonance imaging (fMRI) [4]. EEG is particularly suitable for studies in children due to its non-invasive nature, high temporal resolution, and relative accessibility. In this case, a functional network node is typically defined as an individual EEG channel or a group of topographically close channels, and the edge weight of this graph is the connectivity coefficient between individual nodes [1]. Methodological advances in signal processing, including wavelet-based approaches, offer versatile tools for multiscale characterization of brain signals and functional connectivity [5].

Despite the active development of neuroscience research, a number of fundamental questions remain unanswered. Many studies focus on the analysis of connections in the resting state, which does not address the reorganization of neural networks during various cognitive functions [6]. In contrast, the investigation of functional networks during cognitive task performance can reveal task-related changes in network organization and their relationship with behavioral performance [7]. In particular, the mechanisms of functional network organization during working memory processing in school-age children remain poorly understood. The age range from 8 to 14 years is of particular interest, as it encompasses a period of active maturation of frontoparietal and interhemispheric connections associated with various cognitive functions [8]. However, frequency-specific patterns of functional networks during working memory and their relationship with behavioral performance across this developmental period remain insufficiently understood [9]–[11].

Thus, the goal of this study is to reconstruct and analyze functional networks associated with working memory task solving in children aged 8–14 years.

II. Methods

The experiment was approved by the Immanuel Kant Baltic Federal University Ethics commission (Protocol No. 32 of 04/07/2022), and the parents of the subjects signed a voluntary consent for their children to participate in the experiment. Totally 95 neurotypical school students aged 8-14 years participated in the neurophysiological experiment, divided into three groups depending on age:

1) Group 1 (n = 24, 14 boys and 10 girls, average age is 9.5 ± 0.7 years);
2) Group 2 (n = 28, 17 boys and 11 girls, average age is 11.3 ± 0.6 years);
3) Group 3 (n = 43, 22 boys and 21 girls, average age is 13.1 ± 0.4 years).

During the experiment, an EEG was recorded using 64 leads according to the standard montage ”10-10”, monopolar.

Authorized licensed use limited to: Kant Baltic Federal Univ. Downloaded on October 23,2026 at 15:26:02 UTC from IEEE Xplore. Restrictions apply.

The tasks were completed using a laptop with a touchscreen display.

The experimental task is based on S. Sternberg's paradigm [12], designed to study the processes of working memory: a random set of two-digit numbers and the symbol "*" is shown on the screen. The subject's task is to answer whether the presented number was part of a previously shown set of elements. The difficulty varied depending on the number of numbers in the set. The overall structure of the experiment included three equal blocks. In each block, a series of cognitive tests of different types was presented in random order. Each block began with a 1-minute recording of background activity in a resting state and ended with a 2-minute break. The total duration of the experiment was approximately 45 minutes (excluding the time for electrode placement and instruction—one session lasted approximately 65 minutes in total). During this time, the participant was instructed to avoid talking and minimize motor activity unrelated to answering the tasks. During the break, the student was allowed to rest, but leaving the table was discouraged. If a participant did not want to continue the experiment, they could terminate it early, but data from such sessions were not included in the analysis due to the unequal number of tasks completed compared to the data from other subjects. The design of the experiment is described in more detail in our previously published work [13].

We performed segmentation, i.e., the process of selecting fragments of eeg (epochs) that are significant for subsequent analysis from the recording, with the formation of pairs of epochs of equal duration:

1) "Task" – the epoch with the solution of the problem (the moment from showing the whole sample to making a decision to the subject),
2) "Rest" – the epoch at rest, taken from the period of background activity preceding the corresponding block.

We implemented this segmentation approach in order to take into account brain activity during task solving and at rest when restoring functional brain networks, thereby identifying activity associated with task performance.

We studied the bioelectric activity of the brain within the main frequency ranges of brain rhythms, taking into account the age of the subjects: theta (2.5–7.5 Hz), alpha (7.5–13.5 Hz), and beta (13.5–20.5 Hz) [14]. To determine functional connectivity, the coefficient of the imaginary part of coherence [15] was calculated in pairs for all EEG channels separately in each frequency range studied. Coherence is a widely used measure of synchronization between signals [16]. Since the work evaluated the severity of the functional relationship regardless of the direction of the phase shift, the absolute values of imaginary coherence were used in the subsequent analysis. Based on them, equal matrices of functional connectivity were formed for each subject.

We reconstructed funcrional networks using Network-Based Statistic (NBS) [17] by pairwise comparing functional connectivity matrices calculated for the task period and the corresponding background activity period. A significance level of $p = 0.01$ was used as the primary threshold for individual connections; the statistical significance of network components was assessed at the cluster level at $p = 0.05$. To calculate the topological characteristics of functional networks, connections included in the network identified by the NBS method in the corresponding frequency range were used. For each subject, the values of these connections were selected from the functional connectivity matrix calculated during the task period. Thus, the structure of the analyzed network was determined by the results of the NBS analysis, and the connection weights were determined by individual values of the imaginary part of coherence. To analyze the age-related characteristics of the resulting functional networks and assess their relationship with behavioral indicators, we calculated the average weighted node degree of the brain network [18].

To assess the relationship between behavioral data and network macroparameters, we calculated the average median reaction time of the subjects (the duration from the moment the matrix of numbers was shown to the subject's decision-making, with only correctly completed tasks taken into account). In the correlation analysis, we calculated the Spearman's rank correlation coefficient. A one-way ANOVA was used to assess differences in reaction time between age groups. To assess frequency and age-group differences in mean weighted node degree, we used a mixed-design repeated-measures analysis of variance (RM-ANOVA), with Band as a within-subject factor and Group as a between-subject factor, followed by post-hoc pairwise comparisons with Holm correction for multiple comparisons.

III. Results

A one-way ANOVA revealed a significant effect of age group on reaction time ($F = 21.78, p < 0.001$). Post-hoc pairwise comparisons with Holm correction revealed significant differences between Group 1 and Group 2 ($p_{\mathrm{Holm}} < 0.001$), Group 1 and Group 3 ($p_{\mathrm{Holm}} < 0.001$), and Group 2 and Group 3 ($p_{\mathrm{Holm}} = 0.018$), with reaction time decreasing with age.

A mixed-design RM-ANOVA with the within-subject factor "Band" and the between-subject factor "Group" revealed a significant main effect of Band on the mean weighted node degree ($F = 19.37, p < 0.001$; see Fig. 1a). Post-hoc pairwise comparisons with Holm correction revealed significant differences between the theta and alpha bands ($p_{\mathrm{Holm}} = 0.002$), theta and beta bands ($p_{\mathrm{Holm}} < 0.001$), and alpha and beta bands ($p_{\mathrm{Holm}} = 0.011$). The theta band demonstrated the highest mean weighted node degree compared with the alpha and beta bands. No significant main effect of Group on the mean weighted node degree was observed ($F = 0.1, p = 0.9$). The interaction between Band and Group was not statistically significant ($F = 1.3, p = 0.272$), indicating that the frequency-dependent pattern of mean weighted node degree did not significantly differ between age groups.

Correlation analysis revealed a significant negative relationship between mean reaction time and mean weighted node degree in the alpha band ($\rho = -0.247, p = 0.016$; see Fig. 1b). Thus, higher mean weighted node degree in the

Authorized licensed use limited to: Kant Baltic Federal Univ. Downloaded on October 23,2026 at 15:26:02 UTC from IEEE Xplore. Restrictions apply.

alpha-band network was associated with shorter reaction times. This finding indicates an association between alpha-band functional connectivity and behavioral performance. The result is consistent with the proposed role of alpha-band activity in attentional control and the suppression of task-irrelevant processing during working memory tasks [19]. Furthermore, neurofeedback studies have shown that modulation of attention can affect brain oscillatory dynamics [20].

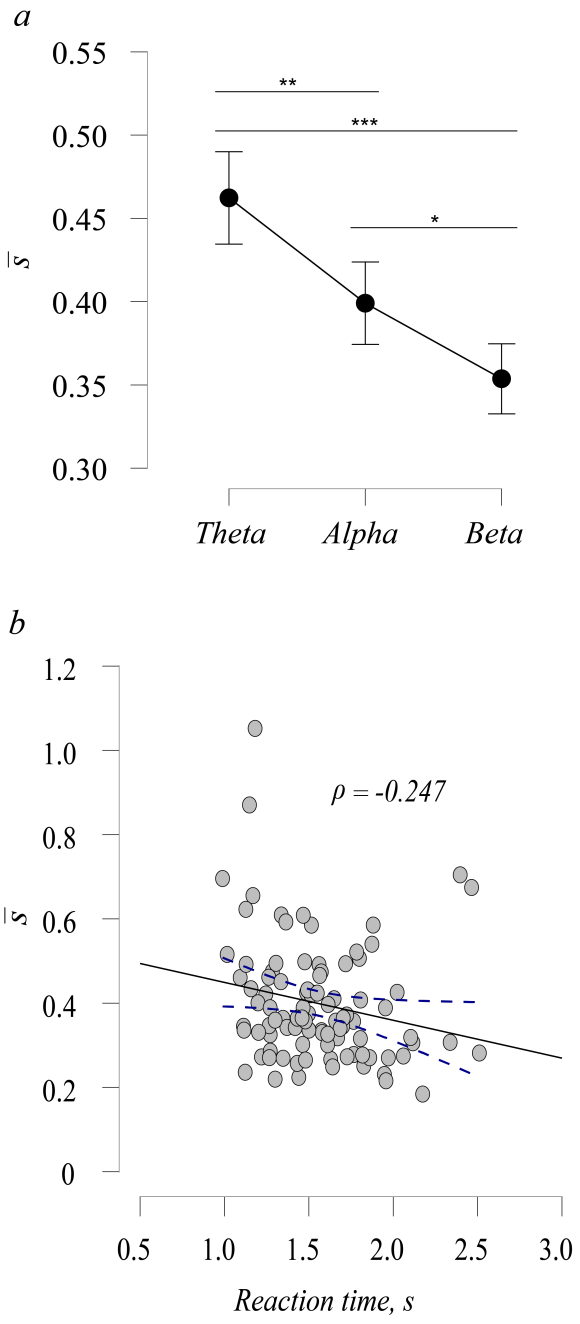


Fig. 1. (a) The graph of the average weighted degree of node $\bar{s}$ depending on the frequency range ($^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; $CI = 95\%$). (b) The scatter plot of the average weighted degree of node $\bar{s}$ with reaction time of the alpha range ($p < 0.05$, Spearman's correlation coefficient ρ and $CI = 95\%$ are shown)

IV. Conclusion

Thus, we identified frequency-specific patterns of functional brain networks associated with working memory task performance in children aged 8–14 years. The mean weighted node degree was highest in the theta band, whereas a significant negative correlation between mean weighted node degree and reaction time was observed in the alpha band ($\rho = -0.247, p = 0.016$). These findings indicate that, although the theta band exhibited the highest mean weighted node degree, individual differences in behavioral performance were specifically associated with alpha-band functional connectivity.

References

[1] A. Hramov, N. Frolov, V. Maksimenko, S. Kurkin, V. Kazantsev, and A. Pisarchik, "Functional networks of the brain: from restoration of connections to dynamic integration," *Usp. Fiz. Nauk*, vol. 191, pp. 614–650, 2021.

[2] S. D. Mayes, R. Kallus, L. R. Bangert, W. Fosco, S. L. Calhoun, and D. A. Waschbusch, "Relationship between sluggish cognitive tempo, iq and academic achievement test scores, and academic impairment in autism, adhd, and elementary school samples," *Child Neuropsychology*, vol. 28, no. 2, pp. 244–265, 2022.

[3] A. Cortés Pascual, N. Moyano Muñoz, and A. Quílez Robres, "The relationship between executive functions and academic performance in primary education: Review and meta-analysis," *Frontiers in psychology*, vol. 10, p. 449759, 2019.

[4] E. C. van Straaten and C. J. Stam, "Structure out of chaos: functional brain network analysis with eeg, meg, and functional mri," *European Neuropsychopharmacology*, vol. 23, no. 1, pp. 7–18, 2013.

[5] L. Kralj, S. Kurkin, H. Lenasi, A. Pavlov, A. Stožer, A. E. Hramov, M. Perc, and M. Gosak, "Wavelet analysis in biomedical research: A versatile tool for multiscale signal characterization and functional connectivity analysis," *Physics of Life Reviews*, vol. 59, pp. 19–47, 2026.

[6] I. Gaudet, A. Hüsser, P. Vannasing, and A. Gallagher, "Functional brain connectivity of language functions in children revealed by eeg and meg: A systematic review," *Frontiers in human neuroscience*, vol. 14, p. 62, 2020.

[7] A. A. Badarin, V. M. Antipov, V. V. Grubov, A. V. Andreev, E. N. Pitsik, S. A. Kurkin, and A. E. Hramov, "Brain compensatory mechanisms during the prolonged cognitive task: fnirs and eye-tracking study," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 17, no. 2, pp. 303–314, 2024.

[8] M. V. Khramova, A. K. Kuc, V. A. Maksimenko, N. S. Frolov, V. V. Grubov, S. A. Kurkin, A. N. Pisarchik, N. N. Shusharina, A. A. Fedorov, and A. E. Hramov, "Monitoring the cortical activity of children and adults during cognitive task completion," *Sensors*, vol. 21, no. 18, p. 6021, 2021.

[9] N. Smirnov, A. Badarin, S. Kurkin, and A. Hramov, "A new electroencephalography marker of cognitive task performance," *Bulletin of the Russian Academy of Sciences: Physics*, vol. 87, no. 1, pp. 108–111, 2023.

[10] A. Badarin, N. Brusinskii, V. Grubov, T. Bukina, S. Kurkin, M. V. Khramova, and A. E. Hramov, "Recurrency time entropy of brain wave rhythms as an indicator of performance on visual search tasks in schoolchildren," *The European Physical Journal Special Topics*, vol. 234, no. 15, pp. 4899–4906, 2025.

[11] N. Brusinsky, A. Badarin, A. Andreev, V. Antipov, and S. Kurkin, "Dynamics of the brain's wave rhythms predict the speed of performing cognitive tasks," *Bulletin of the Russian Academy of Sciences: Physics*, vol. 88, no. 1, pp. 138–141, 2024.

[12] S. Sternberg, "High-speed scanning in human memory," *science*, vol. 153, no. 3736, pp. 652–654, 1966.

[13] V. V. Grubov, M. V. Khramova, S. Goman, A. A. Badarin, S. A. Kurkin, D. A. Andrikov, E. Pitsik, V. Antipov, E. Petushok, N. Brusinskii *et al.*, "Open-loop neuroadaptive system for enhancing student's cognitive abilities in learning," *IEEE Access*, 2024.

[14] J. D. Power, A. L. Cohen, S. M. Nelson, G. S. Wig, K. A. Barnes, J. A. Church, A. C. Vogel, T. O. Laumann, F. M. Miezin, B. L. Schlaggar *et al.*, "Functional network organization of the human brain," *Neuron*, vol. 72, no. 4, pp. 665–678, 2011.

Authorized licensed use limited to: Kant Baltic Federal Univ. Downloaded on October 23,2026 at 15:26:02 UTC from IEEE Xplore. Restrictions apply.

[15] G. Nolte, O. Bai, L. Wheaton, Z. Mari, S. Vorbach, and M. Hallett, "Identifying true brain interaction from eeg data using the imaginary part of coherency," *Clinical neurophysiology*, vol. 115, no. 10, pp. 2292–2307, 2004.
[16] A. E. Hramov, A. A. Koronovskii, M. K. Kurovskaya, and O. I. Moskalenko, "Synchronization of spectral components and its regularities in chaotic dynamical systems," *Physical Review E*, vol. 71, no. 5, p. 056204, 2005.
[17] A. Zalesky, A. Fornito, and E. T. Bullmore, "Network-based statistic: identifying differences in brain networks," *Neuroimage*, vol. 53, no. 4, pp. 1197–1207, 2010.
[18] H. Seidkhani, A. R. Nikolaev, R. N. Meghanathan, H. Pezeshk, A. Masoudi-Nejad, and C. van Leeuwen, "Task modulates functional connectivity networks in free viewing behavior," *NeuroImage*, vol. 159, pp. 289–301, 2017.
[19] W. Klimesch, "Alpha-band oscillations, attention, and controlled access to stored information," *Trends in cognitive sciences*, vol. 16, no. 12, pp. 606–617, 2012.
[20] V. A. Maksimenko, A. E. Hramov, V. V. Grubov, V. O. Nedaivozov, V. V. Makarov, and A. N. Pisarchik, "Nonlinear effect of biological feedback on brain attentional state," *Nonlinear Dynamics*, vol. 95, no. 3, pp. 1923–1939, 2019.

Authorized licensed use limited to: Kant Baltic Federal Univ. Downloaded on October 23,2026 at 15:26:02 UTC from IEEE Xplore. Restrictions apply.