The Relationship Between IQ Level and Functional Brain Network Centrality During Cognitive Activity in Children

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***Abstract*—In the current study, we restored the functional brain networks of children aged 10 to 12 years old when performing cognitive tasks related to learning processes. To calculate connectivity, we chose the method of calculating the imaginary part of coherence (ICOH) in the theta, alpha and beta frequency ranges. To characterize each network, we calculated the main network indicators for them - the average degree of conditionality, the clustering coefficient, efficiency and average centrality. As a result of the search for correlates of network metrics and data on the performance of the tasks of the subjects, we found the presence of positive correlations of network centrality in the alpha frequency range with both the effectiveness of complex cognitive tasks and the overall level of intelligence of the subjects. Thus, the greater integration of the functional network contributes to a more efficient operation of complex cognitive functions.**

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

I. INTRODUCTION

The human brain consists of about 86 billion neurons forming an extremely extensive network through pathways and synaptic contacts [1]. Currently, research is actively underway to study neural interactions, motivated by the fact that specific brain functions are related, rather, to the topology of the neural network as a whole – the so-called brain connectome, and not associated with any one specific structure [2]–[4]. Through the prism of such scientific views, research on higher human nervous activity – cognitive functions - is also actively conducted [5], [6]. Such works, in addition to their fundamental importance in human neuroscience, have applied significance. For example, to take into account the psychophysiological characteristics of students in educational processes [7], or as a diagnostic measure to assess the degree of development of mental abilities in cognitive disorders [8]–[10]. In the context of this issue, it is of particular interest to study the features of the functional connectivity of the actively developing brain of children in cognitive activity, which can have significant potential for improving educational practices: by studying the features of functional brain networks and analyzing integrative processes associated with solving cognitive tasks, it is possible to identify key features of neural activity in the learning process. Traditionally, such an accessible method as conducting cognitive tests is used to assess the level of development of various cognitive human beings (for example, the task of psychomotor alertness [11], however, this approach may be subjective. Therefore, data on brain activity obtained on the basis of noninvasive neuroimaging methods (such as EEG, MEG, fNIRS, fMRI, etc.) can provide a more objective assessment of the cognitive state of the subject [**?**], [12]–[16]. One of the widely used methods for studying brain activity in the framework of neurophysiological research is electroencephalography, which makes it possible not only to study the electrical activity of individual areas of the cerebral cortex, but also to reconstruct the functional networks of interactions of cortical neurons [17], [18]. The main motive for the performance of the presented work was the interest in studying the functional connectivity of brain networks in the most common cognitive activity of children in the learning process (short-term and working memory, visual object search, arithmetic calculations) [5]. The global problem of such scientific research is the study of the psychophysiological state of children in the learning process (solving cognitive problems), including the reconstruction of functional brain networks and the analysis of integrative processes associated with cognitive activity.

II. METHODS

The experimental paradigm is described in detail in a previously published paper. [19] The design of the experiment included tasks associated with various types of cognitive load, the most common in the learning process (visual information retrieval, processing information in short-term memory, the ability to mentally perform arithmetic calculations, as well as the ability to combine these functions to solve complex problems). In addition, a few days after the experiment, the participants took an intelligence test (Raven's Progressive Matrices [20]). As part of the current study, brain activity was analyzed when solving tasks such as "Combined functions". These tasks were a modified version of the Schulte tables [21] The study was approved by the Ethics Committee of the Immanuel Kant Baltic Federal University and the legal representatives of all children signed voluntary informed consent to participate in the study. Initially, the sample included 28 children aged 10-12 years (fifth-grade schoolchildren). However, during the experiment, 6 children decided to refuse to complete all blocks of tasks, citing boredom or fatigue. For this reason, data were selected only from those participants who completed all tasks (22 people as in total, see Fig. **??**.

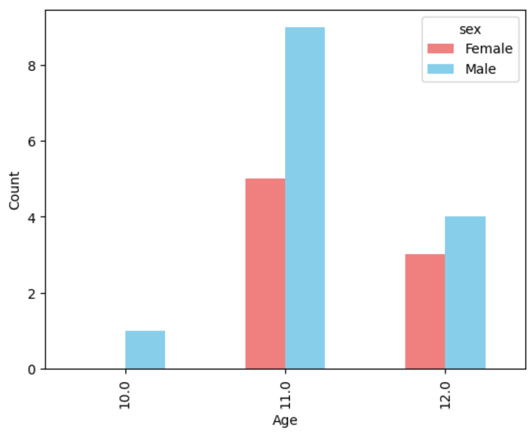

Fig. 1. Age distribution among children.

Analysis of the EEG data was carried out using the "MNE-Python" package (version 1.7.0) [22]. To identify the brain activity associated with the task, we segmented the data as follows: for each task cycle, we got two epochs of equal duration:

1) An EEG epoch when solving a problem (the moment from showing the stimulus to making a decision to the subject);
2) An EEG epoch from the background (when the subject was at rest with his eyes open), taken randomly and equal in duration to the epoch with the completion of the task.

This approach to segmentation was implemented in order to be able to compare brain activity during cognitive load in a resting state and during cognitive load when reconstructing functional brain networks. To calculate connectivity, we used the method for calculating the imaginary part of coherence(ICOH). This method ignores synchronizations caused by in-phase (with zero phase delay) oscillations and takes into account only neural interactions with some phase delay, so this measure reflects more reliable interactions of neural structures [**?**]. Brain activity was studied in the main frequency ranges of electrical brain activity: theta ($4-8$ Hz), alpha ($8-13$ Hz) and beta ($13-32$ Hz). The average metric was calculated for the frequency ranges of interest, for each type of building, for each state of the subject separately (rest period - problem solving period). Thus, we obtained connectivity matrices, which were used to identify the functional network associated with the task for the corresponding frequency range, using the statistical method NBS [23]. Then, for each network, we calculated the main network indicators:

1) Average node degree is the average number of connections (the so-called "edges") that connect a node with other nodes in the network. An integrative metric that reflects the "branching" of the network, i.e. the tendency for extensive synchronization of many neural structures;
2) Clustering coefficient is a measure of how closely connected network nodes tend to form groups of nodes (the so-called "clusters"). It measures the proportion of possible connections between neighboring nodes and is a segregation metric - i.e. the tendency of the network to be more localized within a certain group of nodes;
3) Network efficiency is a measure of the efficiency of information transfer in the network, assessing how quickly information can spread through the network and how long paths are required for communication between nodes;
4) Average centrality is the average central metric of all nodes in the graph.It is an integrative metric.

RESULTS

During the calculations, for each frequency range the connectivity network associated with the solution of the corresponding task type was reconstructed, and the main network characteristics were calculated.

Firstly, we found a positive correlation between the coefficient of average centrality in the alpha range and the proportion of correct answers ($r = 0.427$), which may indicate a connection between network integration in combination with an increased influence on the network of individual clusters on the ability to solve complex problems requiring an integrated approach (see Fig. 2a).

Secondly, we found a direct positive correlation between the IQ and the centrality of the network (Spearman's rank correlation ρ = 0.496) in the α range, which also indicates the existing trend of communication between this network metric and the level of general intelligence of the study participants (see Fig. 2b). This is probably due to the fact that the role of certain network structures (clusters) increases its importance in information processing – this phenomenon may be caused by choosing the most optimal strategy for solving problems, as well as the ability to use more effective strategies for transferring information between neuron structures).

Thus, it can be concluded that the integration of a functional network in the alpha frequency range (the influence of individual clusters on its operation) may lead to a more confident approach to solving complex cognitive tasks. Our observations can be useful in the development of a diagnostic measure to assess the cognitive state of subjects, and also contributes

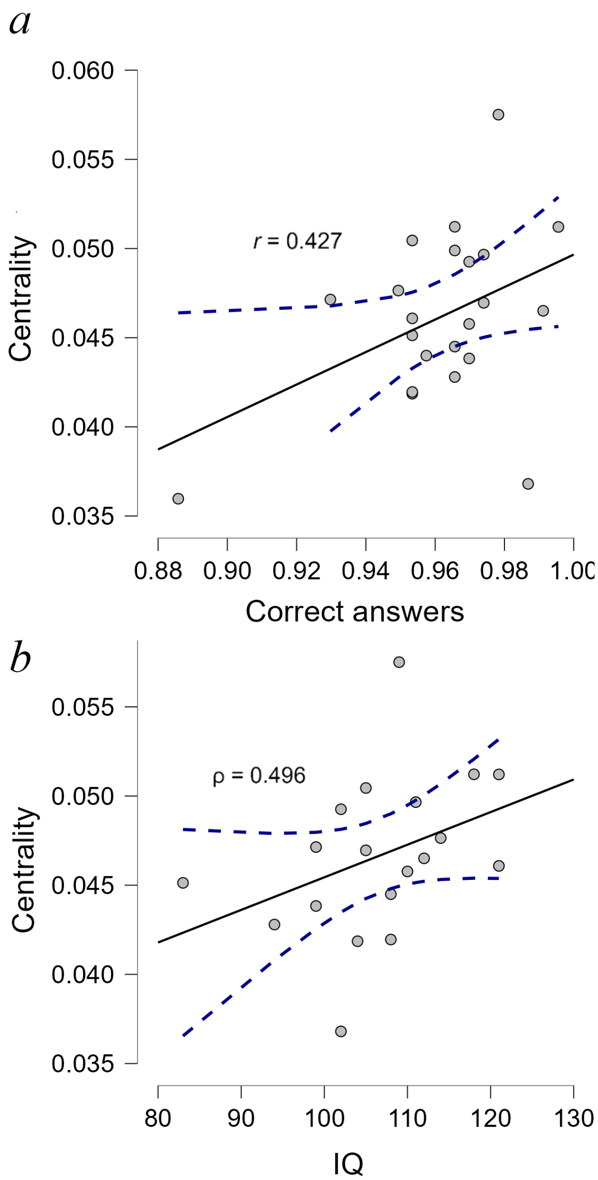

Fig. 2. Graphs of the relationships between centrality and the proportion of correct answers(a, Pearson correlation, $p < 0.05$, $CI = 0.95$) and IQ(b, Spearman's rank correlation, $p < 0.05$, $CI = 0.95$) for the alpha range.

to the understanding of the neurobiological foundations of calculating cognitive functions.

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