Analysis of the Parameters of Multilayer Functional Networks Built on the Basis of Multimodal Data

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***Abstract*—In the current study, we examined the features of multimodal functional brain networks constructed based on EEG and fMRI data in order to identify features associated with the successful processing of sensory information under conditions of uncertainty. We compared the network characteristics between correct and incorrect responses during the performance of the Raven Progressive Matrices task. Using Network-Based Statistics (NBS), we identified significant edge clusters that differed depending on the conditions. An analysis of the importance of features using Random Forest classification with Leave-One-Subject-Out cross-validation revealed that the sum of absolute correlation values and the mean absolute correlation value, as well as the weighted clustering coefficient, were the most informative predictors of task success. These results indicate that successful performance under conditions of uncertainty is primarily related to the overall efficiency of functional connectivity and the integration of the local network, rather than to the size or density of the network.**

***Index Terms*—EEG, fNIRS, functional brain network, multimodal brain data, Raven's Progressive Matrices**

I. Introduction

In neuroscience, functional connectivity of the brain refers to the consistency of neural activity, which is determined using statistical analysis. Studying neural interactions during cognitive activity is of interest for understanding the neurophysiological mechanisms underlying the successful processing of information and decision-making [1], [2]. Multimodal approaches combining electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS) have complementary advantages: EEG provides high temporal resolution of neural oscillations, while fNIRS measures hemodynamic responses that reflect regional cortical activity [3]. Methodological advances in signal processing, including wavelet-based approaches, offer versatile tools for multiscale characterization of brain signals and functional connectivity [4]. Recent studies have revealed hierarchical network disruptions in various neurological and psychiatric conditions, such as schizophrenia [5] and disorders of consciousness [6], as well as early mild cognitive impairment [7], emphasizing the importance of network organization for cognitive function.

Functional networks (sets of brain regions with similar neural activity) are reconstructed using connectivity coefficients calculated based on brain activity data [1]. Recent studies have emphasized the importance of studying the reorganization of networks during cognitive tasks, identifying task-related changes in network organization, and their relationship with behavioral outcomes [8]. However, the mechanisms of multimodal organization of functional networks during complex cognitive tasks involving ambiguous sensory information have not been sufficiently studied.

Raven's Progressive Matrices represent a well-established paradigm for assessing fluid intelligence and abstract reasoning, requiring the integration of visuospatial information and rule discovery under conditions of perceptual ambiguity [9], and frequency-specific and modality-specific patterns of functional networks during the task performance and their relationship with behavioral accuracy remain insufficiently understood [10]–[12]. For detailed network analysis, we chose theta wave activity because its role in working memory and executive control has been fully studied. Studies have shown that theta wave oscillation is regarded as a key neural mechanism. It not only coordinates the operation of working memory function at the level of information sequence organization, but also coordinates the regional integration between the various structures involved in tasks in the brain [13]. When performing tasks that require cognitive control, such as conflict resolution and response inhibition, the intensity of theta waves in the central frontal lobe brain area increases. Studies have confirmed that the theta-wave phase synchronization between the medial prefrontal cortex and the cortical regions involved in the task can transmit cognitive control signals [14]. Considering that the Raven's Progressive Matrix test requires the maintenance and processing of visual spatial information, recognition pat-

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terns, and decision–making under the condition of perceptual uncertainty, that is, the need to mobilize working memory and cognitive control, we will focus on the connection analysis in the theta wave range (4-8 Hz) to identify functional networks based on EEG.

Thus, the goal of this study is to reconstruct and analyze multimodal functional networks associated with successful and unsuccessful performance on Raven's Progressive Matrices task in neurotypical adult people aged 18-32 years.

II. Methods

The experiment was approved by the Immanuel Kant Baltic Federal University Ethics commission. Totally 33 neurotypical subjects aged 18-32 years participated in the neurophysiological experiment.

During the experiment, EEG was recorded using 32 leads according to the standard montage "10–10", and fNIRS was recorded simultaneously using 16 channels. The tasks were completed using a laptop with a touchscreen display. The experimental task was based on Raven's Progressive Matrices task [9], designed to study reasoning and visuospatial processing: participants were presented with a matrix of abstract patterns with a missing piece and were required to select the correct option among several alternatives. Accuracy and reaction time were recorded.

The experiment began with a 1-minute recording of background activity in a resting state and ended with a break. The total duration of the experiment was about 30 minutes. The design of the experiment is described in more detail in our previously published work [15].

We performed segmentation, i.e., the process of selecting fragments of EEG and fNIRS epochs that are significant for subsequent analysis from the recording, forming pairs of epochs of equal duration:

1) "Correct" — epochs with correctly solved tasks;
2) "Incorrect" – epochs with incorrectly solved tasks.

This segmentation approach allowed us to identify activity associated with successful and unsuccessful task performance.

We studied the bioelectrical and hemodynamic activity of the brain in the main frequency bands: the theta signal (4–8 Hz) for EEG and the oxygenated hemoglobin signal (HbO) for fNIRS. To determine the functional relationship, Pearson correlation coefficients were calculated between all pairs of EEG channels, all pairs of fNIRS channels, and cross-modally between EEG and fNIRS channels. Although we used Pearson correlation, other methods such as wavelet-based connectivity analysis can provide complementary multiscale information [4]. Prior to statistical analysis, the correlation matrices were transformed using Fisher's z-transformation (inverse hyperbolic tangent) to normalize the distribution and carry out parametric testing. The absolute values of the correlation coefficients were used to analyze differences in the strength of the relationship, regardless of the sign.

We reconstructed functional networks using Network-Based Statistic (NBS) [16] by pairwise comparing functional connectivity matrices calculated for correct and incorrect response conditions. 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 $p = 0.05$. An anatomical mask was applied to exclude cross-modal edges connecting EEG and fNIRS channels from different anatomical regions, preventing the detection of spurious differences in edges with zero connectivity by construction.

After NBS identified significant edge clusters that differ depending on the conditions (see Fig.1a, 1b), a binary mask was created for each cluster, defining the set of edges included in the significant component. This mask was then used to extract quantitative characteristics of the subgraph at the level of individual trials. For each trial of each subject, a subgraph formed by the edges of the significant cluster was extracted from the original multimodal connectivity matrix, and a number of graph characteristics were calculated. The extracted characteristics included data on the distribution of edge weights (average absolute correlation, standard deviation of absolute correlation, average signed correlation, standard deviation of signed correlation, sum of absolute values, proportion of positive links), structural parameters (number of edges, number of active nodes, number of connected components, density), and topological metrics (transitivity, weighted clustering coefficient, global efficiency, assortativity by degree, spectral radius, algebraic connectivity). A total of 16 characteristics were calculated for each test.

To assess the significance of the extracted graph features, a classification procedure was applied using cross-validation with the Leave-One-Subject-Out (LOSO) method. A random forest classifier with class balancing was used. In each cycle, the data from one subject was used as a test set, while the data from all the others were used for training. This validation scheme prevents information leakage between subjects and allows assessing the model's ability to generalize to new subjects. To determine the contribution of individual features to classification performance, a permutation method was used. In each LOSO cycle, the values of each feature in the test set were randomly shuffled, and the decrease in the ROC-AUC score was assessed compared to the original prediction. The procedure was repeated 10 times for each feature, and the final significance was calculated as the average decrease across all cycles.

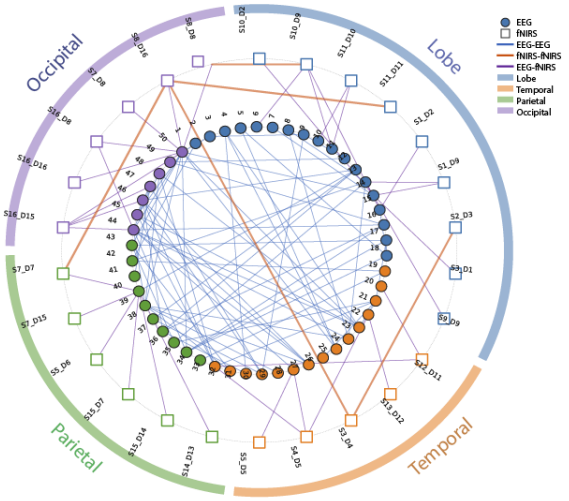
III. Results

The NBS analysis revealed significant clusters of connections that differed depending on whether the response was correct or incorrect (see Fig. 1a and 1b). The identified cluster included connections within the framework of EEG modalities, fNIRS modalities, and cross-modal EEG-fNIRS connections. Visualization showed that the most pronounced differences were localized in the frontal and parietal lobes of the cerebral cortex and were associated with theta EEG rhythms (4–8 Hz) and HbO signals (see Fig.2).

From the initial set of 16 graph characteristics, the permutation importance analysis showed that 10 characteristics

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A



B

Ch. EEG #	Anatomical name	Ch. EEG #	Anatomical name
1	caudalmiddlefrontal-lh	26	inferiortemporal-rh
2	caudalmiddlefrontal-rh	27	middletemporal-lh
3	frontalpole-lh	28	middletemporal-rh
4	frontalpole-rh	29	parahippocampal-lh
5	lateralorbitofrontal-lh	30	temporalpole-lh
6	lateralorbitofrontal-rh	31	temporalpole-rh
7	medialorbitofrontal-rh	32	transversetemporal-lh
8	paracentral-lh	33	transversetemporal-rh
9	parsopercularis-lh	34	inferiorparietal-lh
10	parsorbitalis-lh	35	inferiorparietal-rh
11	parsorbitalis-rh	36	postcentral-lh
12	parstriangularis-rh	37	postcentral-rh
13	precentral-lh	38	precuneus-lh
14	precentral-rh	39	precuneus-rh
15	rostralmiddlefrontal-lh	40	superiorparietal-lh
16	rostralmiddlefrontal-rh	41	superiorparietal-rh
17	superiorfrontal-lh	42	supramarginal-lh
18	superiorfrontal-rh	43	supramarginal-rh
19	bankssts-lh	44	cuneus-lh
20	bankssts-rh	45	cuneus-rh
21	entorhinal-lh	46	lateraloccipital-lh
22	entorhinal-rh	47	lateraloccipital-rh
23	fusiform-lh	48	lingual-rh
24	fusiform-rh	49	pericalcarine-lh
25	inferiortemporal-lh	50	pericalcarine-rh

Fig. 1. (a)The diagram of a significant NBS cluster reflecting differences in the structure of multimodal functional connectivity between the conditions of a correct and an incorrect response when performing a task with Raven's Progressive Matrices. The inner ring corresponds to cortical areas of the EEG (theta range 4–8 Hz, Desikan–Killiany parcellation), the outer ring corresponds to fNiRS channels (HbO). The color of the nodes and arcs reflects the anatomical zone (frontal, temporal, parietal, occipital). The edges between nodes indicate statistically significant differences in functional connectivity: blue indicates EEG–EEG connections, orange indicates fNIRS–fNIRS connections, and purple indicates cross-modal EEG–fNIRS connections. The diagram displays 10% of the edges in the cluster with the largest difference between conditions. (b) The table mapping the numbers of EEG nodes on the diagram to the anatomical names of cortical regions.

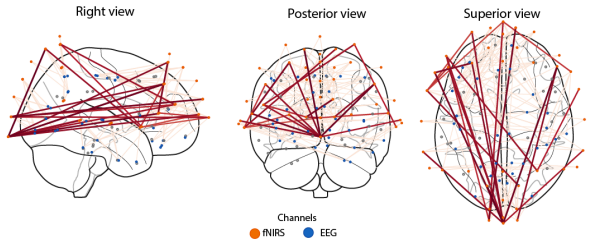


Fig. 2. The graph of statistically significant differences in the structure of multimodal functional connectivity between conditions with correct and incorrect responses when performing tasks with progressive Raven Progressive Matrices, identified using the Network-Based Statistics (NBS).

make a positive contribution to the classification quality. The characteristics with the highest informativeness were those related to the distribution of edge weights: the sum of absolute correlation values ($\Delta ROC - AUC = 0.026$) and the average absolute correlation (0.023), as well as the topological metric weighted clustering coefficient (0.023). The next most informative group consisted of the average signed correlation and the standard deviation of the signed correlation (about 0.010 for each), as well as algebraic connectivity (0.008). A smaller but positive contribution was made by the proportion of positive links, the standard deviation of absolute correlation, the spectral radius, and transitivity (from 0.002 to 0.003). Six characteristics were excluded from further analysis: the number of active nodes and the number of edges were constant for a fixed NBS cluster mask (importance equals zero), and assortativity by degrees, density, global efficiency, and the number of connected components showed negative importance of permutations, which indicates that their inclusion in the model led to noise and worsened the model's generalizability. Thus, we used the final set of 10 characteristics for predictive modeling.

The structure of the obtained set of informational features shows that the difference between correct and incorrect task performance is mainly determined by the integral characteristics of the edge weight distribution and the topological organization of the significant subgraph, rather than by its size or the advantages of the features that reflect the overall strength of functional connectivity (the sum of values). from the absolute correlation values, the average absolute correlation) indicates that successful task performance is mainly associated with the overall level of coordination of actions between the network nodes. The high informativeness of the weighted clustering coefficient, in turn, indicates the importance of local integration: the formation of densely connected subgroups of nodes reflects the coordinated activity of functionally similar regions, which is important for processing complex, uncertain stimuli. The contribution of algebraic connectivity and spectral radius highlights the role of global topological properties of the clusters. The network highlights the role of large-scale integration in ensuring efficient cognitive data processing. The density and number of connected components are not included in the informational characteristics. This fact is consistent with

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the view that cognitive differences manifest themselves in functional connectivity strength and topological organization rather than in the number of connections involved. [17]. This is in line with studies showing that clinical conditions are associated with hierarchical network disruptions rather than global changes in network size [5], [6].

IV. Conclusion

Thus, we identified modality-specific and frequency-specific patterns of multimodal functional brain networks associated with successful and unsuccessful performance on Raven's Progressive Matrices task. The most informative predictors of task success were the sum of absolute correlation values, mean absolute correlation, and weighted clustering coefficient. These findings indicate that, although global network metrics such as density and number of connected components did not differentiate performance, individual differences in behavioral accuracy were specifically associated with overall connectivity strength and local network integration. These results contribute to the understanding of network reorganization in cognitive tasks and may have implications for clinical applications, such as diagnosis of mild cognitive impairment [7].

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