Classification of fluid intelligence levels in schoolchildren based on neurophysiological EEG characteristics

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***Abstract*—We present a comprehensive approach to binary classification of schoolchildren by the level of fluid intelligence based on resting-state electroencephalographic (EEG) data. The study was performed on a sample of 90 schoolchildren aged 8-14 years. As neurophysiological features, we used the detrended fluctuation analysis exponent in the alpha band, averaged across channels of the right frontal region, and topological characteristics of functional networks derived from connectome-based predictive modeling. A systematic comparison of a wide range of classifiers was conducted, including support vector machines, linear and discriminant models, nearest neighbor methods, neural network, and ensemble algorithms. The best result was achieved with Radius Neighbors ($r = 10$): $F1 = 0.778, accuracy = 0.778, AUC = 0.8$. Comparable performance was demonstrated by k-nearest neighbors ($k = 3$) and LightGBM. The obtained results demonstrate the informativeness of combining descriptions of the temporal organization of neuronal activity and functional connectivity for objective classification of cognitive ability levels.**

***Index Terms*—EEG, fluid intelligence, long-range temporal correlations, DFA, functional connectivity, machine learning**

I. Introduction

Objective assessment of individual differences in cognitive abilities is a pressing challenge in neuroscience and artificial intelligence [1], with direct applications in education, where cognitive profiles can guide personalized recommendations for students [2]. Electroencephalography enables non-invasive investigation of brain activity dynamics with high temporal resolution [3]. However, the use of local EEG characteristics alone does not always adequately capture the distributed organization of cognitive processes [4], since general intelligence is increasingly viewed as an emergent property of large-scale brain network organization [5]. A promising extension is the combined analysis of long-range temporal correlations [6] and functional brain connectivity [7], which together provide a multiscale characterization of neural activity [8].

Long-range temporal correlations characterize the persistence of statistical dependence between temporally distant segments of neural activity [9]. To quantify them, we employed detrended fluctuation analysis (DFA). Spatial organization of interactions was assessed using phase locking value (PLV) followed by topological analysis of functional networks [10]. Spontaneous functional connectivity has been repeatedly linked to individual differences in intelligence [11], and connectome-based approaches have shown that fluid intelligence can be predicted from individual connectivity patterns [12], [13]. The combination of these features with machine learning methods enables a transition from the identification of statistical associations to automated classification of subjects.

The aim of the present study was to determine the informativeness of a comprehensive neurophysiological feature space for binary classification of subjects by fluid intelligence level and to select the most effective machine learning algorithm.

II. Materials and methods

A. Subjects and experimental protocol

The study involved 90 schoolchildren aged 8-14 years (41 girls and 49 boys). All participants were students from the same school and had no history of neurological or psychiatric disorders. Cognitive testing included tasks assessing visual search, working memory, mental arithmetic, and combined cognitive functions [14]. Fluid intelligence level was assessed using Raven's Progressive Matrices (RPM). For binary classification, participants were divided into highIQ and lowIQ groups based on the median RPM score.

B. EEG recording and processing

EEG was recorded using a LiveAmp system (Brain Products) with 64 channels arranged according to the international 10-20 system, at a sampling rate of 1000 Hz. Raw recordings were bandpass-filtered in the range of 1-100 Hz and subjected to 50 Hz notch filtering. Artifacts, primarily related to eye movements and cardiac activity, were removed using independent component analysis (ICA).

DFA was calculated for four frequency bands: delta+theta (1-7 Hz), alpha (6-13 Hz), beta1 (13-20 Hz), and beta2 (20-30 Hz). For each narrowband signal, the amplitude envelope

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was extracted using the Hilbert transform, after which a cumulative profile was constructed and detrending was performed across multiple temporal scales. Functional connectivity was assessed using PLV between all pairs of the 64 channels, after which clustering coefficients, global efficiency, and connection strength were computed for each network.

C. Feature space construction

Preliminary selection of neurophysiological features was performed based on the results of statistical analysis and CPM [15]. For classification, we used the DFA exponent in the alpha band averaged over the right frontal channels, as well as the topological characteristics of positive and negative functional networks identified through CPM [16], [17]. The positive network comprised 28 significant connections, while the negative network comprised 29 connections.

The combination of these features simultaneously reflected the temporal organization of neural oscillations and the spatial structure of functional interactions.

D. Classifier testing

To select the optimal algorithm, we performed a systematic comparison of a wide range of models [18]: SVM with linear, polynomial, and radial basis function kernels; logistic regression; linear and quadratic discriminant analysis [19]; k-nearest neighbors; Radius Neighbors; naive Bayes classifier; decision tree; multilayer perceptron; random forest; gradient boosting; AdaBoost; XGBoost; LightGBM; Extra Trees; and stochastic gradient descent. Missing values were imputed with the median, and features were standardized. Stratified 5-fold cross-validation was applied on the training set, and final metrics were computed on a held-out test set comprising 20% of the data. The weighted F1-score served as the primary selection criterion. Additionally, accuracy, balanced accuracy, Matthews correlation coefficient, and AUC were evaluated.

III. Results

Analysis of the initial neurophysiological parameters revealed informative markers associated with cognitive test performance. For DFA, statistically significant clusters were found in the theta and alpha bands, localized predominantly in the centroparietal and right frontal regions. The alpha band in the right frontal area proved most relevant to RPM scores. In the functional connectivity analysis using CPM, positive and negative networks were identified specifically in the alpha band, and their combined activity significantly predicted RPM scores ($R = -0.32, p = 0.002$, LOOCV).

Additional analysis revealed a relationship between temporal and spatial organization of activity: the clustering coefficient of the negative functional network negatively correlated with DFA in the right frontal region in the alpha band ($r = -0.44, p = 1.9 \times 10^{-5}$). For the remaining combinations of network metrics and DFA examined, no statistically significant associations were found.

The main result of the study was the comparison of classifiers. The best performance was demonstrated by Radius Neighbors with radius $r = 10$: $F1 = 0.778, accuracy = 0.778, and AUC = 0.8$. An identical F1 score was obtained for k-nearest neighbors with $k = 3$ ($F1 = 0.778$), while LightGBM achieved $F1 = 0.772$. For the three best models, the standard deviation of F1 across cross-validation folds did not exceed 0.047, indicating stable performance with respect to variations in the training data.

The obtained accuracy significantly exceeded the No Information Rate of 0.533. Thus, the classifiers successfully extracted information related to fluid intelligence level from neurophysiological features and achieved performance above the baseline determined by the class distribution. The advantage of Radius Neighbors was modest compared to k-nearest neighbors and LightGBM, suggesting that multiple algorithmic approaches provided similar levels of informativeness.

The obtained results suggest that the integrated feature space can serve as a basis for automated binary assessment of cognitive ability levels. Importantly, the classification was not based on a single EEG measure, but on a combination of DFA and topological characteristics of functional networks, which were preliminarily selected based on their association with cognitive test performance.

IV. Conclusion

In this study, we developed and tested a comprehensive approach for binary classification of schoolchildren by fluid intelligence level based on EEG data. The feature space included the DFA exponent in the alpha band of the right frontal region and topological characteristics of functional networks identified via CPM. A systematic comparison of a wide range of algorithms showed that Radius Neighbors ($r = 10$) achieved the best overall performance, with $F1 = 0.778$, $accuracy = 0.778$, and $AUC = 0.8$. Comparable results were obtained for k-nearest neighbors and LightGBM, and the low variability of $F1$ across cross-validation folds indicates the stability of the best-performing models.

Thus, the combination of characteristics of long-range temporal organization of neuronal activity and functional connectivity represents a promising feature description for objective classification of cognitive abilities. The developed approach has been implemented in a Python software package and can serve as a foundation for further research on larger samples and for expanding the scope of automated cognitive diagnostics [20], including its integration into neuroadaptive systems that support students' learning [21].

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