Using long-range temporal correlations in the brain to predict intellectual development in children

Alexander Kuc
Baltic Center for Artificial Intelligence and Neurotechnology
Immanuel Kant Baltic Federal University
Kaliningrad, Russia
kuc1995@mail.ru

Vadim Grubov
Baltic Center for Artificial Intelligence and Neurotechnology
Immanuel Kant Baltic Federal University
Kaliningrad, Russia
vvgrubov@gmail.com

Artem Badarin
Baltic Center for Artificial Intelligence and Neurotechnology
Immanuel Kant Baltic Federal University
Kaliningrad, Russia
badarin.a.a@mail.ru

***Abstract*—In this study, we employed electroencephalographic recordings to predict intelligence quotient (IQ) in children aged 8 to 10 years. The intelligence quotient (IQ) was measured using Raven's progressive matrices. The detrended fluctuation analysis (DFA) method was employed to quantify the autocorrelations of the signal. The results demonstrated that the exponent of DFA in the frontal brain area in the alpha frequency range is correlated with IQ. Consequently, DFA provides supplementary data regarding IQ-related cognitive functions and can be employed as a means of objective assessment of a child's intelligence.**

***Index Terms*—long-range temporal correlations, detrended fluctuation analysis, electroencephalogram, intelligence quotient, regression analysis**

I. Introduction

The period of childhood is of great significance, as it is during this time that the brain undergoes active development, acquiring various cognitive skills [1], [2]. Therefore, in order to accurately assess the intellectual development of children, it is essential to identify objective biomarkers that will reliably predict cognitive function [3], [4]. The use of objective biomarkers will allow for individual differences in children, thereby improving the predictive accuracy of cognitive assessment methods, including the use of machine learning algorithms [5], [6]. One such reliable biomarker is brain electrical activity (EEG), which can be used to accurately assess a child's level of intellectual development [7].

Neuroimaging techniques based on electroencephalography (EEG) have a broad range of practical applications in diverse fields, including the diagnosis of neurological and psychiatric disorders [8], the investigation of cognitive processes within the brain [9], [10], and the study of neuroplasticity [11]. These techniques can also be employed in conjunction with machine learning [12], [13] and artificial intelligence approaches [14], [15].

This work is supported from the Russian Science Foundation (project 24-71-00106)

In this study, we employ the detrended fluctuation analysis (DFA) method, which in contrast to traditional methods of investigating neurophysiological signals, such as frequency-time analysis [16], [17] and functional reconstructions [18], this approach is used to evaluate long-range temporal correlations in the brain and delineates the temporal stability of oscillatory processes within the brain. The DFA method has been extensively applied in recent years to analyse electroencephalographic (EEG) signals, with the objective of studying the complexity and dynamics of neural activity in the brain [19]. This method has found wide application in the field of medical diagnostics [20] and the study of neural dynamics in various neurological diseases [21].

The objective of this study was to investigate the potential of the DFA exponent as a reliable predictor of the level of intellectual development in schoolchildren. We have shown the relationship between DFA, which is a measure of long-term temporal correlations of brain activity, and IQ scores of experimental participants.

II. Materials and methods

A. Experiment

The study involved 24 schoolchildren aged between 8 and 10 years (10 girls and 14 boys), who were in their third and fourth grade at the same school.

The experimental study comprised two distinct parts: testing the subjects with Raven's Progressive Matrices (RPM) and a two-minute electroencephalogram (EEG) recording at rest. The rest EEG provides insight into the subject's current cognitive state [22]. The RPM is a non-verbal test that is commonly employed to assess an individual's general intelligence and abstract thinking abilities. The test comprises 60 multiple-choice questions, divided into five sets of increasing difficulty. Each question is presented in the form of a visual stimulus, typically a pattern of dots, lines, or geometric figures, with a

2024 8th Scientific School Dynamics of Complex Networks and their Applications (DCNA) | 979-8-3503-9083-4/24/$31.00 ©2024 IEEE | DOI: 10.1109/DCNA63495.2024.10718435

missing component. The test-taker is required to select one of the presented options to complete the picture. The test results are converted into an intelligence quotient (IQ) according to the age of the test taker.

B. EEG recording and preprocessing

EEG signals were recorded utilising a ”LiveAmp“ device (Brain Products, Germany) with Ag/AgCl ”ActiCap“ active electrodes. A total of 64 EEG channels were recorded on the surface of the head according to the international ”10-10“ arrangement scheme [23]. EEG signals were recorded at a sampling rate of 1000 Hz and subsequently processed by band-pass filters with cut-off frequencies of 1 Hz and 100 Hz, in addition to a 50 Hz band-pass filter. Physiological artefacts related to heart rate and eye movements were removed by independent component analysis (ICA), utilising the FieldTrip software package for MATLAB [24].

C. Analysis of experimental data

Long-range temporal brain correlations were estimated utilising the DFA method [25]. DFA is a scaling analysis method [26] used to estimate long-range temporal correlations of power-law form. It involves the fitting of a slow nonstationarity, which is considered to be a trend, with further characterisation of fluctuations around the signal profile, which deviate from the trend. DFA is a subtype of multifractal signal analysis that is actively applied to analyze EEG signals [27]. The Neurophysiological Biomarker Toolbox was employed to assess long-term temporal correlations. The raw electroencephalogram (EEG) signal was filtered in the following frequency bands: delta and theta (1-7 Hz), alpha (6-13 Hz), beta-1 (13-20 Hz), and beta-2 (20-30 Hz) using a finite impulse response (FIR) filter. The amplitude envelope was obtained using the Hilbert transform. The filter order was set equal to $2/f$, ensuring that at least two cycles of oscillations with frequency f [Hz] were covered by the filter window. Oscillations were computed in each frequency range using overlapping windows of h = 50% from 0.8 to 30 s, and the DFA exponent was found by fitting from 2 to 15 s. For each subject, DFA exponents were averaged over the brain regions of interest: frontal, central, occipital-parietal, and temporal.

III. Results

We performed linear regression to assess the potential of DFA exponents to predict IQ. The dependent variable was IQ, while DFA exponents averaged across brain areas and frequency bands were used as predictors. We trained two types of models: in the first group, DFA exponents averaged across brain areas for each frequency band were used as predictors; in the second group, DFA exponents averaged across frequency bands for each brain areas were used as predictors. In the first instance, DFA in the alpha band demonstrated a significant predictive capacity for IQ ($R2 = 0.62, p = 0.002$). A post-hoc analysis revealed that only the frontal DFA made a significant contribution to the prediction ($\beta = 0.66, p = 0.002$). In the second case, only frontal DFA was found to be able to predict IQ ($R2 = 0.551, p = 0.006$). Subsequent analysis revealed that only the alpha band exhibited a significant correlation with the outcome variable ($\beta = 0.687, p = 0.006$).

The results indicate that alpha-band frontal DFA can predict IQ. Figure 1 illustrates the relationship between frontal alpha band DFA and IQ. Each subject's values are shown along with the regression line (solid line) and 95% confidence interval (dashed lines). The Pearson correlation coefficient (r) between these variables is also reported.

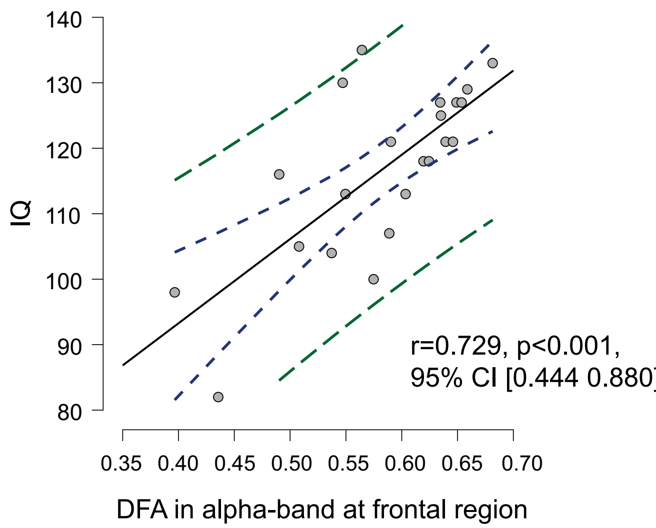

Fig. 1. The correlation between IQ and DFA. The data are presented as individual values (dots), a regression line (solid line), and 95% confidence intervals for training and prediction data (dashed lines).

IV. Conclusion

A study conducted with a group of 8-10 year old schoolchildren revealed that an index of long-range temporal correlations in the time series of brain neural activity, in particular the DFA exponent in the frontal area in the alpha frequency range, can serve as a reliable predictor of a child's IQ. The findings have the potential to inform the development of personalised educational methods [28]. The DFA can be recorded using a small number of non-invasive electrodes at rest, thus facilitating its implementation with portable EEG headsets [29]. The use of IQ and DFA as biomarkers in personalised education enables teachers to gain insight into their students' cognitive abilities, thereby allowing them to tailor the educational programme to their specific needs.

V. Acknowledgments

The authors would like to thank Vladimir Maksimenko for his substantial contribution to the results obtained in this work.

References

[1] T. Klingberg, “Childhood cognitive development as a skill,” *Trends in cognitive sciences*, vol. 18, no. 11, pp. 573–579, 2014.

[2] 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.

[3] S. A. Kurkin, V. V. Grubov, V. A. Maksimenko, E. N. Pitsik, M. Khramova, and A. E. Hramov, "System for monitoring and adjusting the learning process of primary schoolchildren based on the eeg data analysis," *Informatsionno-upravliaiushchie sistemy [Information and Control Systems]*, no. 5 (108), pp. 50–61, 2020.

[4] V. A. Maksimenko, A. E. Runnova, M. O. Zhuravlev, P. Protasov, R. Kulanin, M. V. Khramova, A. N. Pisarchik, and A. E. Hramov, "Human personality reflects spatio-temporal and time-frequency eeg structure," *PloS one*, vol. 13, no. 9, p. e0197642, 2018.

[5] A. K. Bowe, G. Lightbody, A. Staines, and D. M. Murray, "Big data, machine learning, and population health: predicting cognitive outcomes in childhood," *Pediatric research*, vol. 93, no. 2, pp. 300–307, 2023.

[6] A. Batmanova, A. Kuc, V. Maksimenko, A. Savosenkov, N. Grigorev, S. Gordleeva, V. Kazantsev, S. Korchagin, and A. E. Hramov, "Predicting perceptual decision-making errors using eeg and machine learning," *Mathematics*, vol. 10, no. 17, p. 3153, 2022.

[7] 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.

[8] M. S. Kabir, S. Kurkin, G. Portnova, O. Martynova, Z. Wang, and A. Hramov, "Contrastive machine learning reveals in eeg resting-state network salient features specific to autism spectrum disorder," *Chaos, Solitons & Fractals*, vol. 185, p. 115123, 2024.

[9] 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.

[10] A. N. Pisarchik, V. A. Maksimenko, A. V. Andreev, N. S. Frolov, V. V. Makarov, M. O. Zhuravlev, A. E. Runnova, and A. E. Hramov, "Coherent resonance in the distributed cortical network during sensory information processing," *Scientific Reports*, vol. 9, no. 1, p. 18325, 2019.

[11] A. Chepurova, A. Hramov, and S. Kurkin, "Motor imagery: How to assess, improve its performance, and apply it for psychosis diagnostics," *Diagnostics*, vol. 12, no. 4, p. 949, 2022.

[12] A. V. Andreev, S. A. Kurkin, D. Stoyanov, A. A. Badarin, R. Paunova, and A. E. Hramov, "Toward interpretability of machine learning methods for the classification of patients with major depressive disorder based on functional network measures," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 33, no. 6, 2023.

[13] V. V. Grubov, S. I. Nazarikov, S. A. Kurkin, N. P. Utyashev, D. A. Andrikov, O. E. Karpov, and A. E. Hramov, "Two-stage approach with combination of outlier detection method and deep learning enhances automatic epileptic seizure detection," *IEEE Access*, 2024.

[14] O. E. Karpov, E. N. Pitsik, S. A. Kurkin, V. A. Maksimenko, A. V. Gusev, N. N. Shusharina, and A. E. Hramov, "Analysis of publication activity and research trends in the field of ai medical applications: Network approach," *International Journal of Environmental Research and Public Health*, vol. 20, no. 7, p. 5335, 2023.

[15] E. N. Pitsik, V. A. Maximenko, S. A. Kurkin, A. P. Sergeev, D. Stoyanov, R. Paunova, S. Kandilarova, D. Simeonova, and A. E. Hramov, "The topology of fmri-based networks defines the performance of a graph neural network for the classification of patients with major depressive disorder," *Chaos, Solitons & Fractals*, vol. 167, p. 113041, 2023.

[16] O. E. Karpov, V. V. Grubov, V. A. Maksimenko, S. A. Kurkin, N. M. Smirnov, N. P. Utyashev, D. A. Andrikov, N. N. Shusharina, and A. E. Hramov, "Extreme value theory inspires explainable machine learning approach for seizure detection," *Scientific Reports*, vol. 12, no. 1, p. 11474, 2022.

[17] O. E. Karpov, V. V. Grubov, V. A. Maksimenko, N. Utaschev, V. E. Semerikov, D. A. Andrikov, and A. E. Hramov, "Noise amplification precedes extreme epileptic events on human eeg," *Physical Review E*, vol. 103, no. 2, p. 022310, 2021.

[18] S. Kurkin, N. Smirnov, E. Pitsik, M. S. Kabir, O. Martynova, O. Sysoeva, G. Portnova, and A. Hramov, "Features of the resting-state functional brain network of children with autism spectrum disorder: Eeg source-level analysis," *The European Physical Journal Special Topics*, vol. 232, no. 5, pp. 683–693, 2023.

[19] J. W. Kantelhardt, E. Koscielny-Bunde, H. H. Rego, S. Havlin, and A. Bunde, "Detecting long-range correlations with detrended fluctuation analysis," *Physica A: Statistical Mechanics and its Applications*, vol. 295, no. 3-4, pp. 441–454, 2001.

[20] M. Bachmann, J. Lass, and H. Hinrikus, "Single channel eeg analysis for detection of depression," *Biomedical Signal Processing and Control*, vol. 31, pp. 391–397, 2017.

[21] O. Sysoeva, V. Maximenko, A. Kuc, V. Voinova, O. Martynova, and A. Hramov, "Abnormal spectral and scale-free properties of resting-state eeg in girls with rett syndrome," *Scientific Reports*, vol. 13, no. 1, p. 12932, 2023.

[22] A. K. Kuc, S. A. Kurkin, V. A. Maksimenko, A. N. Pisarchik, and A. E. Hramov, "Monitoring brain state and behavioral performance during repetitive visual stimulation," *Applied Sciences*, vol. 11, no. 23, p. 11544, 2021.

[23] A. Kuc, V. V. Grubov, V. A. Maksimenko, N. Shusharina, A. N. Pisarchik, and A. E. Hramov, "Sensor-level wavelet analysis reveals eeg biomarkers of perceptual decision-making," *Sensors*, vol. 21, no. 7, p. 2461, 2021.

[24] A. Kuc, V. Maksimenko, A. Savosenkov, N. Grigorev, V. Grubov, A. Badarin, V. Kazantsev, S. Gordleeva, and A. Hramov, "Studying perceptual bias in favor of the from-above necker cube perspective in a goal-directed behavior," *Frontiers in Psychology*, vol. 14, p. 1160605, 2023.

[25] R. Hardstone, S.-S. Poil, G. Schiavone, R. Jansen, V. V. Nikulin, H. D. Mansvelder, and K. Linkenkaer-Hansen, "Detrended fluctuation analysis: a scale-free view on neuronal oscillations," *Frontiers in physiology*, vol. 3, p. 23105, 2012.

[26] G. Guyo, A. Pavlov, E. Pitsik, N. Frolov, A. Badarin, V. Grubov, O. Pavlova, and A. Hramov, "Cumulant analysis in wavelet space for studying effects of aging on electrical activity of the brain," *Chaos, Solitons & Fractals*, vol. 158, p. 112038, 2022.

[27] V. A. Maksimenko, A. Pavlov, A. E. Runnova, V. Nedaivozov, V. Grubov, A. Koronovslii, S. V. Pchelintseva, E. Pitsik, A. N. Pisarchik, and A. E. Hramov, "Nonlinear analysis of brain activity, associated with motor action and motor imaginary in untrained subjects," *Nonlinear Dynamics*, vol. 91, pp. 2803–2817, 2018.

[28] A. A. Fedorov, S. A. Kurkin, M. V. Khramova, and A. E. Hramov, "Neurotechnology and artificial intelligence as key factors in the customization of the lifelong learning route," *Informatics and education*, vol. 38, no. 3, pp. 5–15, 2023.

[29] J. Xu and B. Zhong, "Review on portable eeg technology in educational research," *Computers in Human Behavior*, vol. 81, pp. 340–349, 2018.