Characterizing ADHD-Related Inhibitory Control Deficits via Multidimensional EEG Signatures

Negin Gholamipourbarogh (Negin.Gholamipourbarogh@ukdd.de)[1], Annet Bluschke (Annet.Bluschke@ukdd.de)[2], Christian Beste (Christian.Beste@ukdd.de)[3]

[1,2,3]Cognitive Neurophysiology, Department of Child and Adolescent Psychiatry, Faculty of Medicine, TU Dresden, Dresden, Germany

Abstract

Attention-Deficit/Hyperactivity Disorder (ADHD) is a neurodevelopmental condition characterized by persistent difficulties in attention regulation and behavioral control. Although electroencephalography (EEG) has provided valuable insights into the neural correlates of ADHD, capturing the full complexity of its underlying brain dynamics requires more advanced analytical approaches. In this study, we employed non-negative tensor decomposition to examine multi-dimensional EEG data collected during a Go/NoGo task. This method revealed distinct neural signatures in individuals with ADHD, particularly involving posterior alpha and theta oscillations during early attentional engagement and later stages of inhibitory control. These findings challenge the traditional focus on fronto-central theta activity and underscore the potential relevance of posterior oscillatory dynamics in the development of more targeted neurofeedback interventions for ADHD.

Keywords: ADHD; EEG; inhibitory control; tensor decomposition; alpha; theta

Introduction

Attention-Deficit/Hyperactivity Disorder (ADHD) is a common neuropsychiatric condition marked by difficulties in cognitive control, particularly response inhibition (Posner et al., 2020). EEG research has elucidated these challenges by revealing disruptions in neural oscillations—especially in theta and alpha bands—linked to attention and impulse regulation (Barry et al., 2003; Cowley et al., 2022). However, traditional analysis approaches often fail to account for the complex, multidimensional structure of EEG data (Baijot et al., 2017)—particularly the trial-by-trial fluctuations that are a hallmark of ADHD (Arnett et al., 2023).

In this proof-of-concept study, we applied nonnegative tensor decomposition to EEG data collected during a Go/NoGo task to better capture these complexities (Cong et al., 2015; Gholamipourbarogh et al., 2024). By analyzing patterns across time, frequency, channel, and single trials, we identified distinct neural signatures of ADHD, particularly concerning intra-individual variability. Using machine learning, these features were used to distinguish ADHD participants from neurotypical controls, pointing toward new possibilities for EEG-based diagnostic tools.

Methods

Participants and Task – We included 59 adolescents with ADHD (age = 10.38 ± 2.31) and 63 neurotypical participants (age = 13.18 ± 2.86), diagnosed according to ICD-10 criteria. All participants completed a 20-minute Go/NoGo task, where they were instructed to press a button for “DRÜCK’” (Go) and withhold responses to “STOP” (NoGo). The task involved 248 Go and 112 NoGo trials, with a 500 ms response window.

EEG Analysis – After preprocessing, we converted EEG data into a four-dimensional tensor capturing channels, frequencies, time points, and single trials, based on 40 correct trials per participant. Using wavelet analysis (0.5–25 Hz), we extracted time-frequency representations and applied non-negative CP decomposition (Wang et al., 2021) to uncover spatial, spectral, temporal, and trial-level features. To ensure reliability, we determined the number of components using a stability-based method. Stability analysis involved repeated tensor decompositions with varied initializations, using co-clustering and a stability index to identify reliable components and determine the optimal model order (Hu et al., 2021). The rusulting trial-level features were then used in a machine learning classifier, trained and tested separately to avoid bias. We ranked feature importance using the Fisher score (Sun et al., 2021). The Fisher score selects features that best separate classes by maximizing between-class variance and minimizing within-class variance, with higher scores indicating greater discriminative power. Figure 1 illustrates the diagram of classification procedure (Gholamipourbarogh et al., 2025).

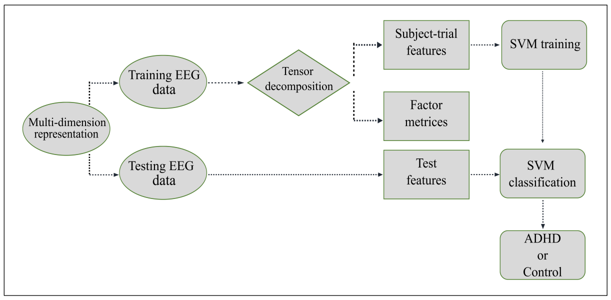

Figure 1: A schematic representation of the EEG data analysis workflow.

Results

Using non-negative tensor decomposition, we identified EEG patterns that effectively differentiated individuals with ADHD from neurotypical participants. The stability analysis was performed, incrementing the number of components (R) from 3 to 50 with 30 iterations per R-value to assess reproducibility via a stability index computed through tensor spectral clustering. The highest stability index (0.915) was achieved with 15 components, which was then used for classifying ADHD versus neurotypical subjects.

Subsequently, a support vector machine (SVM) classifier was trained using features extracted from the tensor. Applying 5-fold cross-validation, the model achieved an average classification accuracy of 77.4%, successfully distinguishing ADHD from control participants at the single-trial level.

We ranked components using the Fisher score to identify the most informative neural features. One component was consistently identified as an artifact and removed before classification. The remaining components showed distinct spatial, spectral, and temporal brain-related characteristics. Figure 2 represents the key neural features for the component with the highest Fisher score.

Notably, components with high discriminative value showed activity in the theta and alpha frequency bands, particularly within parietal and occipital regions, and around 300 ms post-stimulus—time windows and regions linked to attentional processing and inhibitory control.

These findings demonstrate that tensor-based EEG analysis can reveal rich, multidimensional neural patterns linked to ADHD and may contribute to the development of more objective, data-driven diagnostic approaches.

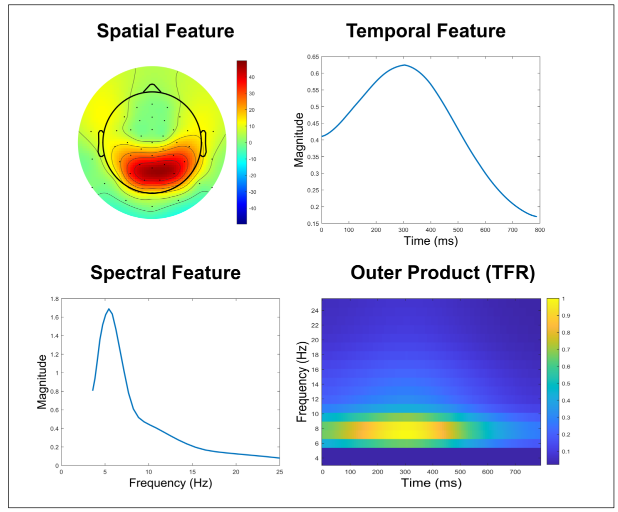

Figure 2: The spatial, temporal, spectral feature and outer product of component associated with the highest Fisher score.

Conclusion

this study demonstrates that EEG tensor decomposition reveals critical neurophysiological insights into response inhibition deficits in ADHD that extend beyond traditional analyses. The findings underscore that disruptions in inhibitory control arise early during attentional selection and persist into later response control stages, with posterior theta and alpha band activities playing a more decisive role than the traditionally emphasized fronto-central theta. These insights suggest that neurofeedback treatments may be more effective if they shift focus from fronto-central to posterior brain regions.

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