Decoding Brain Waves: EEG Attention Detection Across Performance Levels

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1. Introduction

Excessive screen time has been linked to increased hyperactivity and attention problems, raising concerns over attention deficits [1]. While much research focuses on attention disorders, less is known about the neural patterns of individuals with strong focus and concentration. Understanding these brain wave dynamics could provide insights into cognitive resilience and strategies for sustaining attention. To bridge this gap, we developed an EEG-based attention detection pipeline that quantifies cognitive states through EEG data analysis. By examining fluctuations in individual brain waves during an attention-driven gameplay task, we explore event-related potentials to uncover the neural mechanisms distinguishing high and low performers.

Our analysis revealed several key findings, with Beta activity being the most significant across all five brain wave bands. Specifically, high performers showed a gradual decrease in Beta activity from EEG onset to peak gameplay, while low performers exhibited an increase in Beta activity as the gameplay progressed. Furthermore, our dynamic time warping clustering revealed that lower performers were predominantly grouped with higher standard deviation of Alpha power and high Beta wave activity, suggesting a potential link between elevated Beta activity and reduced attention performance.

2. Substantial section

2.1 Related work

Previous studies have explored EEG-based attention classification using machine learning models. [2] classified attention into two states (attention vs. non-attention) with 12 participants, while [3] examined EEG activity across five brain wave bands in 10 participants, distinguishing between relaxed and attentive states using a Stroop Color-Word Test. While these studies echo some of our findings regarding Beta band activity, our approach extends this research by incorporating a dynamic gameplay paradigm with cooldown and burst periods, capturing event-related potentials (ERPs) and brain wave fluctuations in real-time cognitive tasks. With a larger participant pool of size 31, this study provides a more comprehensive analysis of attention-related brain activity across different performance levels.

2.2 Methodology

EEG data were collected using the Muse 2 headband while participants played a custom-designed attention game developed in Pygame. The game featured increasing difficulty, randomised burst phases, and a cooldown period after 60 seconds to assess attention fluctuations. Additionally, the game incorporates adaptive difficulty, where players with higher scores experience an increased obstacle fall speed. EEG signals were recorded in real-time via the MuseLSL API [4] and synchronised with gameplay events, allowing precise alignment of brain wave activity with performance.

Following data collection and initial preprocessing, we applied Discrete Wavelet Transform (DWT) via band pass filtering [5] to analyse distinct brain wave bands—Delta (1-4 Hz), Theta (4-7 Hz), Alpha (8-12 Hz), Beta (13-30 Hz), and Gamma (>30 Hz)—each associated with different cognitive states. These wavelet coefficients provide insights into cognitive load and attention shifts during gameplay.

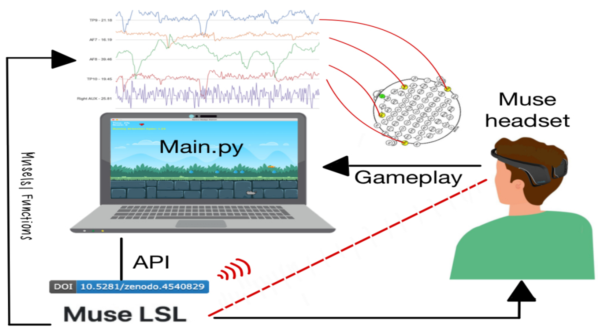

Fig. 1: Icon Description of Data Collection Process

2.3 Key Findings

2.3.1 Cognitive Adaptation in High-Scoring Players

The analysis of Beta power over two critical gameplay phases—5 seconds at the start and 5 seconds before cooldown—reveals distinct patterns between high and low scorers. Participants were classified based on the median score, with high scorers scoring above and low scorers below this threshold (black dotted line in Figure 2). High scorers exhibit a significant decrease in mean Beta power as the game progresses ($t = 2.2815$, $p = 0.0457$), suggesting better cognitive adaptability as gameplay intensity rises. In contrast, low scorers showed no significant change (p = 0.1901), indicating a differing attentional response to increasing difficulty.

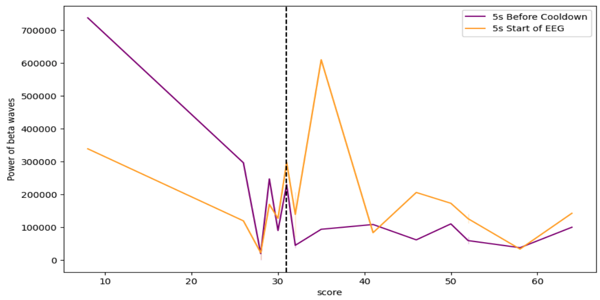

Fig. 2: Mean Beta Power between start of gameplay vs peak of gameplay

2.3.2 *Beta and Alpha Band Activity in Relation to Game Performance*

Beta band analysis revealed significant fluctuations in low scorers, with a marked increase from 35–40s to 40–45s before the cooldown phase at 55s (t = -2.4218, p = 0.0385), coinciding with peak gameplay intensity. In contrast, high scorers showed no significant increase in Beta power despite rising game difficulty.

Following the cooldown period, high scorers exhibited a significant decrease in Beta power from 62–71s to 64–73s, suggesting a greater ability to return to baseline levels. Given the association between high Beta activity and anxiety [6], the ability of high scorers to effectively regulate their stress may be a key factor contributing to their superior performance. Notably, a preceding increase in Alpha band activity from 58–64s to 61–67s (t = -2.5918, p = 0.0291) right after suggests a potential inverse relationship between Alpha and Beta bands, where enhanced relaxation during cooldown may facilitate Beta reduction, aiding stress regulation [7].

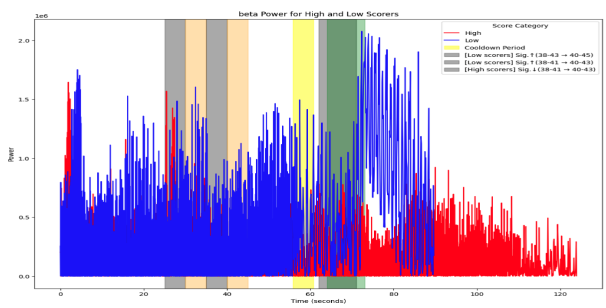

Fig. 3: Beta Power during gameplay between high and low scorers

2.3.3 *Clustering High and Low Performers Using Dynamic Time Warping*

Clustering analysis using Dynamic Time Warping on Alpha and Beta waves revealed notable distinctions between high and low performers:

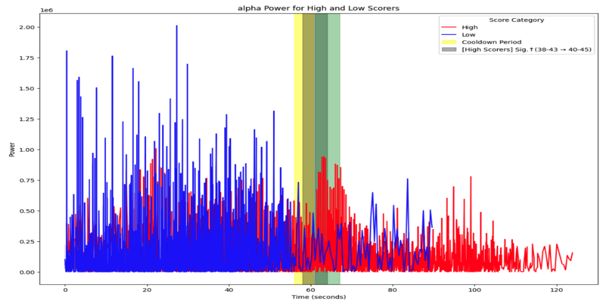

Fig. 4: Alpha Power during gameplay between high and low scorers

- **Alpha Waves**: Cluster 0 which comprises six low scorers, exhibited higher overall mean Alpha power and greater power variability. Analysis of cluster centroids over time revealed that increased Alpha power fluctuation accurately identifies low performers but does not distinguish high performers (100% precision but low recall).
- **Beta Waves**: For Beta waves, the precision was 85%, with one high scorer incorrectly clustered with the group of 6 low scorers in cluster 0. Analysis of the cluster centroids showed that the group of low scorers consistently exhibited higher Beta power across time intervals, further linking higher Beta waves with poorer performance.

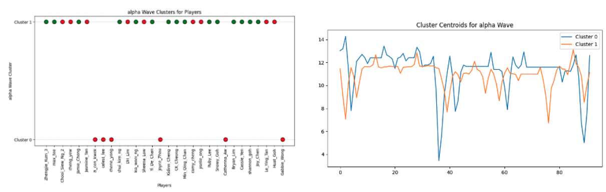

Fig. 5: Clustering of Alpha Waves

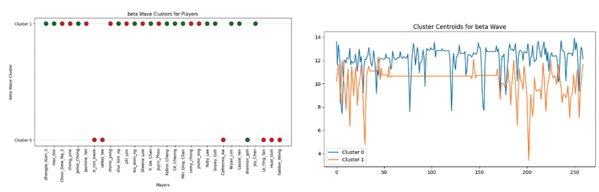

Fig. 6: Clustering of Beta Waves

2.4 *Conclusion*

Our findings highlight the crucial role of Beta waves in attention-driven performance, with high and low performers differing in their ability to regulate Beta activity. The observed inverse relationship between Alpha and Beta waves also suggests that targeting heightened Alpha brain waves may help reduce Beta waves to enhance focus in attention tasks.

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