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# Attention biomarker based on wave rhythm stability

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***Abstract*—This paper presents an analysis of data from a neurophysiological experiment involving various cognitive tasks. The study conducted a statistical analysis of wave rhythm stability and correlated it with average reaction time. The findings confirmed the validity of a previously identified biomarker based on the variance of wavelet energy in EEG signals, demonstrating its effectiveness in reflecting attentional characteristics. This research enhances our understanding of the relationship between wave rhythms and cognitive performance, thereby contributing to the assessment of cognitive load.**

***Index Terms*—EEG, neurophysiological experiment, cognitive testing, brain wave rhythms**

## I. Introduction

Assessing the effectiveness of learning is a crucial aspect of education and pedagogy. Various methods and approaches are employed to evaluate the extent to which learners have achieved their goals and to measure their progress in acquiring knowledge and skills.

One of the most common methods used to assess learning effectiveness is testing the knowledge and skills acquired through completing assignments on covered topics. Additionally, methods for analyzing students' personal qualities are employed to evaluate the effectiveness of learning [1], [2]. However, these approaches have several limitations, with standardization being the primary constraint.

In the pursuit of more personalized methods for assessing cognitive characteristics, attention has shifted towards analyzing brain activity. The dynamics of brain activity in different sensory areas can provide significant insights into the cognitive abilities of the brain [3]–[8]. This analysis is implemented through the use of an electroencephalogram (EEG) [9]–[12].

One of the advantages of EEG is its ability to provide real-time feedback [13]. For instance, it can determine whether a trainee is in a state of focus or distraction, enabling training to be tailored to enhance concentration.

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Furthermore, EEG can be employed to measure the emotional response to learning. It can detect the level of stress or engagement during the learning process.

When analyzing EEG signals, researchers typically distinguish periodic oscillations in various frequency ranges known as wave rhythms. These wave rhythms are specific patterns of electrical activity that reflect the collective dynamics of neurons in the brain. Changes in the amplitude and frequency of these wave rhythms can indicate different states of the brain.

Energy changes within different wave rhythms are frequently utilized as biomarkers in the development of brain-computer interfaces [14]–[16]. These energy changes facilitate the analysis and extraction of information regarding brain states and activity.

The current study builds upon the previous work by [17] and aims to investigate the proposed biomarker within the context of various cognitive load types.

## II. Methods

A neurophysiological experiment was conducted to assess elementary cognitive functions and the simultaneous utilization of these functions in a task. A group of 24 children, aged 9-10 years and without any health issues, participated in the study. The experiment comprised three parts, each consisting of six blocks of tasks presented in a random order: one for visual search, one for working memory, one for mental arithmetic, and three for a combination of these functions.

The focus of this study was on a visual search task implemented in the form of a Schulte table, where participants were required to locate a specific two-digit number among 25 numbers shown in advance.

A 64-channel EEG was recorded using electrodes placed according to the international 10-10 system. The EEG signals were sampled at a frequency of 500 Hz. A 50 Hz notch filter was applied to the signals to eliminate noise from the power grids.

The stability of the wave rhythms was calculated as follows. Firstly, each of the three task blocks was divided into ten equal time intervals with a precision of 1 ms. An additional

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2-second duration was added to both ends of these intervals to compensate for any edge effects.

Next, the wavelet surface was computed using the formulas described in [17]. The wavelet transform was performed separately within four frequency ranges: 1-4 Hz (delta), 4-8 Hz (theta), 8-14 Hz (alpha), and 14-30 Hz (beta).

The resulting surfaces were then averaged across time and frequency. However, to avoid edge effects, 1000 data points (equivalent to 2 seconds) were excluded from both ends of the time series, which were added during the previous step.

From the frequency-time wavelet spectrum, the frequency-averaged energies within standard ranges were calculated. To determine their dispersion, the following approach was employed: each task block was divided into ten equal time segments, and the dispersions between these ten values were separately calculated for each wave rhythm.

To conduct a variance analysis of repeated measurements, the data underwent pre-processing in the form of a z-score procedure to reduce inter-individual variability. The resulting values were then correlated with the average response time. Spearman's correlations were used to examine the relationship among individuals within the first block of tasks. To analyze the experiment's dynamics and explore relationships between blocks, the method of repeated correlations was employed. The electroencephalogram data from each channel were tested independently of each other.

## III. Results

The analysis of variance of repeated measurements revealed statistically significant differences between channels across all frequency ranges. Additionally, significant differences were observed between blocks in the alpha and beta ranges, as well as interference between blocks in the theta range.

Subsequently, we conducted repeated correlation analyses to examine the relationship between response time and channel variance. In the alpha range, correlations were observed in channels FC4, Fz, and O2. In the beta range, correlations were identified in channels Fz, FC1, Pz, Cz, FC2, and P5. In the delta range, correlations were detected in channels F2, FC2, PO8, and PO4. In the theta range, correlations were found in channels FC2 and Fz.

Furthermore, Spearman correlation analysis was performed for the first block of tasks to explore the relationship between channel variance and mean response time. In the alpha range, correlations were observed in 24 channels, and Figure 1 depicts a topographic map illustrating these correlations. In the beta range, correlations were found in channels F7, TP9, and FT7. In the delta range, a correlation was detected in the Pz channel. In the theta range, correlations were observed in channels F3, TP10, Cz, and F1.

## IV. Conclusions

This study discovered a correlation between the stability of alpha-range brain activity in the temporal lobes during a visual search task and the mean response time. This finding suggests that the stability of alpha rhythms could serve as a biomarker for predicting cognitive decline based on wave rhythm dynamics. Furthermore, the study examined the real-time dynamics of this biomarker during the experiment, indicating its potential utility for immediate assessment.

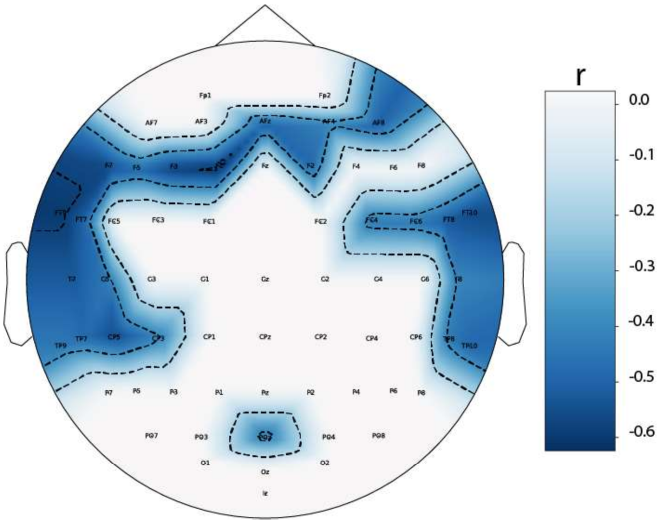


Fig. 1. Topographic map illustrating correlations between average response time and energy variance of alpha rhythms during the visual search task.

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