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# Using Brainwave Entropy to Evaluate Visual Search Performance in School-Aged Children

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***Abstract*—This paper analyzes data from a neurophysiological experiment based on a visual search task. The study investigates methods for predicting response time based on the entropy of the energies of key brain rhythms, such as theta, alpha, and beta, in different brain regions. The aim is to develop methods for predicting task performance efficiency using neurophysiological parameters.**

***Index Terms*—EEG; Schulte table; wavelet analysis; machine learning; entropy**

## I. Introduction

Visual information processing involves a wide range of cortical structures in the brain, including sensory, associative, and motor areas [1], [2]. These structures work together to ensure the effective integration of sensory signals and cognitive processes such as attention, perception, and memory [3]. Therefore, studying brain activity is crucial for gaining a deep understanding of the mechanisms underlying visual information processing [4]. Research on neural activity in these regions reveals the dynamics of interneuronal interactions and functional connections, which, in turn, contributes to understanding the key principles of cognitive architecture that enable successful performance in visual tasks, even in complex environments.

Various neurophysiological monitoring methods are used to analyze these processes and other brain activity, including near-infrared spectroscopy (NIRS) [5], eye-tracking [6], electroencephalography (EEG) [7]–[11], magnetic resonance imaging (MRI) [12], and other techniques. These methods provide detailed insights into brain activity and its functional organization, offering valuable data for studying cognitive processes related to visual perception. For instance, multichannel EEG can provide information about the functional connectivity between different brain regions, which is particularly important for analyzing network activity and distributed information processing. Additionally, multimodal research approaches, which combine multiple techniques such as EEG and fNIRS [5], [6], [13], allow for a more comprehensive understanding of how different brain networks interact and process sensory information across various modalities, providing a richer picture of cognitive function.

One of the advantages of EEG is its ability to provide real-time feedback. This allows its signals to be used for brain-computer interface applications [8], [9].

Simultaneously, most basic research, although it provides quite detailed information about the analysis of brain activity during visual search tasks, does not answer how to predict the performance of this kind of tasks.

The present study is a continuation of the [14] and aims to explore ways of predicting response times using recurrent wavelet energy measures of wavelet rhythms in a visual search task.

## II. Methods

A neurophysiological experiment was conducted to test elementary cognitive functions and the ability to use them simultaneously in a task. A group of 52 children aged 8-12 years without health problems was recruited for the study. Each of the three parts of the experiment consisted of the following six blocks of tasks arranged in random order: one on visual search, one on working memory, one on mental arithmetic, and three on a combination of these functions. A detailed description of the entire experiment is described in [14].

The purpose of the study in this paper was a visual search task realized in the form of a Schulte table, in which the subject had to find a two-digit number shown to him in advance among 25 numbers. Only the first block of this type of task was considered in order to reduce the influence of such factors as accumulated fatigue.

A 64-channel EEG was recorded using electrodes placed according to the international scheme 10-10. The sampling frequency of EEG signals during recording was 500 Hz. The signals were filtered with a 50 Hz filter to exclude noise from power grids. Energy of rhythms was calculated as follows. First, the first block of visual search tasks was taken, to which 2 seconds were added on both sides to compensate for the influence of the edge phenomena region in the future. After that, the wavelet surface was calculated based on the formulas given in [10]. The wavelet transform was performed in the alpha (8-14 Hz) and beta (14-30 Hz) bands. After that, the obtained surfaces were averaged by frequency, but to avoid edge effects, 1000 points (2 seconds) were excluded from both ends of the time series, which were additionally added in advance at the previous step. Frequency-averaged energy values were calculated from the time-frequency wavelet spectrum. Based on these energies, entropy was calculated according to the formulas specified in the [15].

The wavelet energy was calculated in Matlab using the fieldtrip module [16].

The vertical entropies were calculated in Python using the PyRQA module [15].

## III. Results

A correlation analysis was performed, showing a number of correlations between behavioral and physiological characteristics, namely between response times and energy entropy values in the alpha (8-14 Hz) and beta (14-30 Hz) bands.

Channels in which significant correlations were found were used as the basis for entropy-based response time predictions.

The performance of different machine learning methods, namely Ordinary Least Squares regression, Lasso regression, and Ridge regression, was compared.

Training was conducted using a cross-validation approach with k-fold equal to 5.

The relative forecast deviation was taken as a performance metric, calculated using the formula:

$$w = \frac{\sum_{i=1}^{52} \mid RT_{pred}^{i} - RT_{real}^{i} \mid}{\sum_{i=1}^{52} RT^{i}} \cdot 100\%$$

As a result, it was found that the linear regression method shows the worst result (w = 27.4), while Lasso and Ridge show comparable results (w = 14.5 and w = 14 respectively).

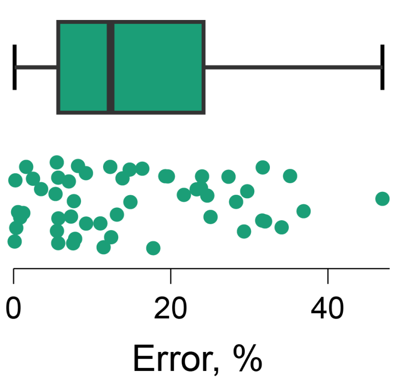


Fig. 1. Distribution of normalized deviation of predicted response time from actual response time

Future plans are to investigate other machine learning methods to determine the most effective one.

## IV. Conclusion

Thus, the Lasso and Ridge methods were found to predict response times based on entropy energies with reasonable accuracy. This extends the ability to predict changes in cognitive ability dymanics using neurophysiological parameters.

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