Detecting fatigue indicators from electroencephalogram data during prolonged cognitive load

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***Abstract*—Identifying and monitoring indicators of fatigue during various cognitive exercises is an important task in the field of cognitive load research and human performance optimization. Fatigue monitoring allows to evaluate the degree of subject's involvement in the process and improve the efficiency of task performance. The current study compared two methods to determine potential indicators of fatigue during different cognitive tasks in 21 subjects. The first method is based on an algorithm for calculating the relative power of electroencephalographic activity $(\alpha + \theta)/\beta$. The second method is based on electrooculogram extraction and analysis of various blink characteristics. In particular, the positive amplitude-velocity ratio (pAVR) was evaluated. The applicability of the algorithms to fatigue detection in cognitive tasks was compared.**

***Index Terms*—mental fatigue, cognitive task, working memory task, electrooculography, blink duration, blink amplitude**

I. Introduction

Fatigue is one of the factors contributing to decreased cognitive performance. Increased fatigue can also indicate a low degree of subject's involvement in the process of performing a task. It is a major but usually neglected factor that increases the number of errors and omissions in performance. Therefore, there is an ongoing effort to find an effective method to detect fatigue in workers and learners. Thus, the determination and control of the degree of fatigue are extremely important both in the development of brain-computer interfaces for various purposes [1], [2] and in neurophysiological studies to account for the fatigue factor [3]–[8].

Literature review showed that most often various biological signals such as EEG, EOG, ECG [9]–[13] are used to detect fatigue. Much of this research focuses on fatigue and sleepiness during monotonous vehicle driving. There are also a number of studies aimed at fatigue in office work [14]. However, the algorithms in the study data estimate fatigue over long time intervals of several hours. They are not effective for cognitive loads of less than one hour. Therefore, this study aims to identify an algorithm that can detect fatigue in a subject while performing cognitive tasks within one hour.

The experiment proposed in this paper was conducted with 21 subjects aged between 11 and 13 years old. The experiment consisted of three blocks with four tasks of different types:

1) Mental arithmetic - solving simple math questions;
2) Working memory - memorizing a set of numbers;
3) Visual search - finding a number in a table;
4) Combined functions - solving, memorizing and finding numbers in a table.

Within one block, the tasks and complexities were shuffled randomly. Each task aimed at testing different cognitive functions. The total duration of one block of the experiment is 16 minutes.

II. Methods

A. EOG characteristics

One approach to assessing fatigue is to analyze electrooculogram (EOG) data [14]. However, the installation of additional electrodes for taking the oculogram signal is not always possible and significantly complicates the research process, since their installation imposes additional restrictions on human movements. To solve this problem, in Kleifges K. [15] proposed a method for automated extraction of oculomotor component. The method is based on the extraction of the ICA component from electroencephalogram (EEG) data, which fully reflects the nature and main components of the electrooculogram signal. After extracting the required component, the signal is analyzed and then the required ocular features are extracted.

To extract the electrooculogram signal from the electroencephalogram, the data decomposition method using Independent Component Analysis (ICA) implemented in the MNE software package [16] was used in the current work. The "FastICA" method presented in Hyvärinen's work [17] used as an algorithm to extract the oculomotor component. To achieve a more accurate and efficient identification of independent components using the FastICA method, the EEG signal was pre-cleaned of low-frequency drift and high-frequency noise

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using FIR filters in the range of 1-40 Hz. This frequency range is due to the specificity of the oculomotor activity retrieval task [15] (i.e., the period of one blink cannot be lower than 1 s and does not exceed 0.025 s).

After decomposing the EEG signals into independent components, it is necessary to identify the component related to oculomotor activity. For this purpose, an iterative z-score method was used. In this method, the z-score of component scores is calculated and components whose z-score exceeds a threshold value are masked. This process is repeated until no suprathreshold component remains. The channels located in the frontal area, Fp1 and Fp2, were used to calculate the component with the most pronounced correlation with oculomotor activity.

Then, the obtained EOG signal is filtered and cleaned from various frequency artifacts. For this purpose, the "agarwal2019" [18] method of the neurokit2 software package [19] was used. This method is presented in Agarwal's work [18] and can be used to prepare electrooculographic data for further analysis. The neurokit method was used to search for blink moments (peaks) from the cleaned EOG data with threshold set to threshold = 0.3. The threshold determines the distance (RMSE) between each blink and the template. The amplitude (A) to peak closure velocity (PCV) ratio of blinks was calculated as an indicator of fatigue. This characteristic (AVR) was presented in the work of Johns [20] and defines a measure of sleepiness that also reflects the degree of fatigue. To calculate this characteristic, the "eog features" function of the neurokit2 software package was used to obtain the positive amplitude to velocity ratio (pAVR). The positive amplitude-to-velocity ratio represents the ratio of the maximum blink amplitude to the maximum velocity (rate of change) during an upward blink. These metrics are measured in centiseconds. It is worth noting that measures A and PCV are related to the same distance units, their ratio can be derived from uncalibrated measurements.

B. EEG characteristics

In the recent years, researchers have investigated different types of fatigue countermeasure technologies, which include development of electroencephalography (EEG) algorithms to detect fatigue [21], [22]. Also, Artaud [23] found that EEG is one of the most reliable indicators of fatigue, and therefore this approach is promising [22].

In this paper we used the algorithm proposed by Eoh [21] and validated by Budi [24] which is based on analyzing the frequency components of EEG recordings in delta, theta, alpha and beta bands. In their research, Budi et al [24] compared several different fatigue detection algorithms by examining the ratios of fast and slow waves. They found that the $(\alpha+\theta)/\beta$ algorithm shows a greater change in fatigue characterization and could potentially be used for fatigue detection.

In our study, the required frequency ranges were chosen as: θ (4 - 8 Hz), α (8-13 Hz), β (13 - 22 Hz). All 64 channels of the EEG data were then sectioned into 2-s epochs. Then an algorithm was used to automatically reject bad epochs described in Mainak's paper [25]. The brain region was divided into three zones: parietal (P1, P2, P3, P4, P5, P6), frontal (F1, F2, F3, F4, F5, F6) and central (C1, C2, C3, C4, C4, C5, C6). After that, a spectral analysis was performed for each epoch and zone in the frequency range (4-30 Hz) using the "multitaper" [26] method. After that, the power ratio $(\alpha+\theta)/\beta$ averaged for all channels of each zone was calculated. This value was then calculated for each experiment within a block.

III. Results

The total average elapsed time of the experiment was 67 min $\pm$ 8 min. From the study by Gillberg, [27], 30 min of monotonous driving activity has been found to induce fatigue during driving. However, the cognitive load offered in this study did not affect the change in EEG power $(\alpha+\theta)/\beta$ over time. The RM ANOVA statistical test showed no significant results as shown in Table I.

TABLE I
CORRELATION TABLE

Factor	Sphericity Correction	df	F	p
Block	None	2.000	0.104	0.901
	Greenhouse-Geisser	1.323	0.104	0.818
Zone	None	2.000	17.280	$<.001$
	Greenhouse-Geisser	1.880	17.280	$<.001$
Block * Zone	None	4.000	1.041	0.391
	Greenhouse-Geisser	2.877	1.041	0.379

We found that the relative energy does not change from block to block for all zones investigated. This may mean that the $(\alpha+\theta)/\beta$ algorithm is not suitable for fatigue detection in such experiments.

Another method based on the EOG study showed more promising results. Figure 1 shows the change in pAVR value by block.

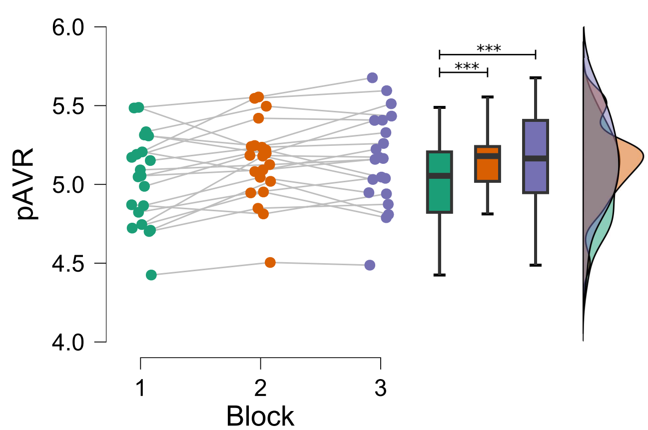

Fig. 1. Change in pAVR characterization by block. pAVR is the ratio of maximum amplitude to maximum blink velocity. The symbol * denotes statistical significance in post hoc analysis using t-test with Holm's correction for multiple comparisons (*** - $p<0.001$).

We analyzed the change in pAVR response throughout the experiment and averaged for each task. RM ANOVA test showed statistically significant results shown in Table II.

TABLE II
WITHIN SUBJECTS EFFECTS

Factor	Sphericity Correction	df	F	p
Block	None	2	9.819	$< .001$

This result may suggest that to identify indicators of fatigue when using cognitive tests it is better to analyze the pAVR characteristic instead of the $(\alpha + \theta)/\beta$ algorithm.

CONCLUSION

As a result of our study, we compared two approaches to identify indicators of fatigue from electroencephalogram data. The statistical test showed that the characteristic (pAVR) obtained by analyzing the oculogram varies more with time than $(\alpha + \theta)/\beta$. This may indicate that it is better to use the pAVR method to detect fatigue in experiments with cognitive load.

ACKNOWLEDGMENT

The work was supported by the Russian Science Foundation (Grant No 23-72-10016).

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