2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Cognitive performance drop detection during daily activities using EEG

Jorge A. Ramírez Castillo[1] and Juan M. Chau[2]

Abstract— **Investing long hours in a cognitively demanding activity without adequate rest has been shown to lead to a decline in cognitive capacity. For this reason, it is crucial to know the moments in which the mental performance is low, to disconnect and recover. This paper presents the design of brain signal processing pipeline using electroencephalographic (EEG) signals to detect cognitive performance drops during sessions that require low physical activity, to determine when users should pause the execution of their current task to take a rest. The developed system is adaptable to any user without requiring prior training. The evaluation considers three mental states: attention, mental fatigue and stress as the most representative; these mental states were re-referenced using the first five minutes of each recording as a calibration period, before applying a set of rules to determine cognitive performance drops. The results showed that, for sixty-two monotonous driving simulation sessions (78.5 $\pm$ 22.4 minutes), the detection time occurred at 35.3 $\pm$ 18.9 minutes in 80.6% of the sessions, and for three studying sessions (30, 20 and 30 minutes each) the detection time occurred at 11.9, 12.3 and 8.3 minutes, respectively.**

I. INTRODUCTION

Investing long hours in cognitive demanding activities, like studying or driving without adequate rest, has been shown to lead to a decline in cognitive performance [1]. As a consequence, people experience mental fatigue, are easily distracted, feel anxiety or simply postpone the activities they are performing. Depending on the type of activity, this can cause them to be unproductive or even endanger their lives.

Cognitive psychology describes the state of mind as a dynamic construction that can vary depending on the circumstances and be affected by cognitive, behavioural and emotional factors [2]. Some of the most representative mental states to understand the cognitive capacity of people are attention, fatigue and stress [3]. Attention is related to the ability to stay focused and process the information received [4]. Mental fatigue manifests when the person reaches the limit of their information processing capacity and the task becomes a demanding process, and turns into a strenuous activity [5]. Stress, is the body reaction to an stimulus, affecting the way a person performs and perceives the task [6].

For activities that demand a cognitive load, the mental states mentioned above generally evolve in the following way across subjects. At the beginning, people tend not be fully engaged with the task at hand, as it takes approximately 20 minutes for a person to completely focus in the activity they are performing; mental fatigue will still be low, as it tends to increase over time; and the body will be warned of the situation and will provide the energy start handling it [5][7]. Moments later, the levels of attention will be optimal; mental fatigue and stress will start to increase, because the subject may have acquired a certain level of competence and will be focused on the task, but at the same time will be making an effort trying to adapt to the stimuli. In the final period, boredom and monotony will lead to a state of hypovigilance and poor perfomance, because the prolongued cognitive activity causes a deterioration in the ability to process stimuli and information, producing a feeling of drowsiness and lack of motivation, and since energy levels cannot be maintained for long periods of time, stress will manifest itself cognitively and physically affecting the subject [6][8].

Researchers have used several methods to detect mental states from eletrophysiological data. One of these methods is the combination of the spectral power of frequency bands to obtain neurophysiological indices that are capable of qualitatively represent mental states and generate representations through trends. To represent the processes of attention, some ratios like beta to alpha [9] or theta to alpha [10] can be used; while for the state of fatigue, some of the used indices are theta-plus-alpha to beta ratio [11] and theta to beta ratio [12]. When it comes to stress, some of the existing methods are the frontal asymmetry of different channels and coherence of signals [13][14]. Other relevant methods to detect these states are statistical methods [15] or machine learning classifiers [16]. However, these require a large number of recordings per subject to train the data correctly and are subject-dependant, which turns analyzing different users' data into a more time-consuming experimental protocol to adapt the system to an specific user.

In this paper, a novel approach for the detection of the early period of low cognitive performance, based on a neurophysiological indices trend analysis during low physical activitiy sessions (person sitting comfortably and not making sudden movements), is proposed.

II. METHODS

Two datasets were considered for this work: the first one was recorded by Cao et al. [17] to design and test the method, and the second one was specifically recorded for validation of the proposed method.

A. Dataset 1

Twenty-seven volunteers, ages 25$\pm$4.2, without visual impairments and no record of sleep problems or drug abuse

[1]Jorge A. Ramírez Castillo is with the with the Facultad de Ciencias e Ingeniería, Pontificia Universidad Católica del Perú, Lima, Peru jaramirezc@pucp.edu.pe

[2]Juan M. Chau is with is with the Facultad de Ciencias e Ingeniería, Pontificia Universidad Católica del Perú, Lima, Peru jmchau@pucp.edu.pe

were recruited. The task involved keeping a vehicle in the centre of the lane in a visually monotonous four-lane road environment with no traffic and random lane departure events. Subjects were asked not to ingest alcohol, stimulants or do strenuous exercise before participating in the experiment.

Sixty-two recordings sampled at 500 Hz were obtained with a a 32-channel wired Ag/AgCl electrode Compumedical NeuroScan Quik-Cap. Electrodes were placed according the 10/20 system for a 90-minute session.

B. Dataset 2

Two students, ages 22 and 23, from Pontificia Universidad Católica del Perú (PUCP) participated voluntarily in three sessions of the experiment in total, while studying for their evaluations. They were asked not to have a record of psychiatric or drug use disorders and not to ingest substances such as caffeine, alcohol, tea or cigarettes or intense physical activities (e.g. sports) 48 hours before the tests.

Three recordings were obtained using a 32 dry electrode g.Nautilus. Electrodes were placed according to the 10/20 system and recorded the subject's brain activity at 500 Hz.

C. Mental states representations

The Fast Fourier transform (FFT) was applied over time windows with a length of three seconds and 50% overlap. Then, the average absolute power $P_{X_i}(f)$ in the frequency bands of interest $[f_L, f_H]$ was calculated at each time point over a subset of n channels X. The frequency ranges for each band are as follows: theta (θ) $\in$ [4,8] Hz, alpha (α) $\in$ [8,13] Hz and beta (β) $\in$ [13,30] Hz. This function I, is displayed in equation 1.

$$I_{f\in[f_L,f_H]}(X) = \sum_{i=1}^{n} \sum_{f=f_L}^{f_H} \underbrace{2*|FFT(X_i)|^2}_{P_{X_i}(f)} \tag{1}$$

Some attention processes are related to the changes in the spectral power of OZ and PZ [18][19][20]. Specifically, changes in the beta and alpha bands provide valuable information about the activity affinity [10]. The attention index (AI), is calculated using the beta to alpha ratio over the aforementioned channels, as observed in equation 2.

$$\text{AI} = \frac{I_\beta(OZ, PZ)}{I_\alpha(OZ, PZ)} \tag{2}$$

Mental fatigue is associated with an increment in the spectral power of theta and alpha bands in the temporal and occipital lobes [11], and the reduction of the spectral power of beta band in the parietal and temporal lobes [21]. The fatigue index (FI), was calculated with equation 3, using T7, T8, TP7, TP8, PZ, OZ, T3, PZ, and T4 channels.

$$\text{FI} = \frac{I_\alpha(TP7, T3, TP8, T4, OZ) + I_\theta(TP7, T3, TP8, T4, OZ)}{I_\beta(T3, PZ, T4)} \tag{3}$$

The frontal cortex is related to stress and other emotional processes [14]. Prior studies evidenced that, in the presence of stress, the spectral power in right frontal channels increase while in the left channels decreases [13][22]. The stress index (SI) was calculated through the frontal asymmetry of F7 and F8 channels, as presented in equation 4.

$$\text{SI} = \log(I_\alpha(F8)) - \log(I_\alpha(F7)) \tag{4}$$

D. Detection of low cognitive performance

The data was preprocessed and analyzed using MATLAB R2019b and Simulink, using a 0.5-50 Hz finite impulse response bandpass filter. To smooth and remove outliers for each mental state values during the calibration and evaluation period, represented by S_c and S_e, respectively, there was applied a moving median filter.

Througout the calibration period, represented by $c \in [0, 5[$ min, $\vec{S}_c$, the mean $\mu(\vec{S}_c)$ and the standard deviation $\sigma(\vec{S}_c)$ were calculated and used as baseline values. Then, the z-score was applied for the following data S_e, where $e \in [5, \infty[$ is the evaluation period, to obtain each of the re-reference said mental states S'_e as presented in equation 5.

$$S'_e = \frac{S_e - \mu(\vec{S}_c)}{\sigma(\vec{S}_c)} \tag{5}$$

Considering t_f, t_s and t_a as the representation of the time values in which the increasing trend of fatigue, stress and attention is mantained, respectively; a performance drop can be identified if either of the following conditions is true: $t_f >= T_f$ and $t_a <= T_a$, $t_s >= T_s$ and $t_a <= T_a$, $t_f >= T_f$ and $t_s >= T_s$. T_f, T_s and T_a are the max time limit values for each mental state. Figure 1 shows an example of the processing of the mental states for a subject from dataset 1, over a 72-minute session, for which the cognitive performance drop happens at approximately 41 minutes.

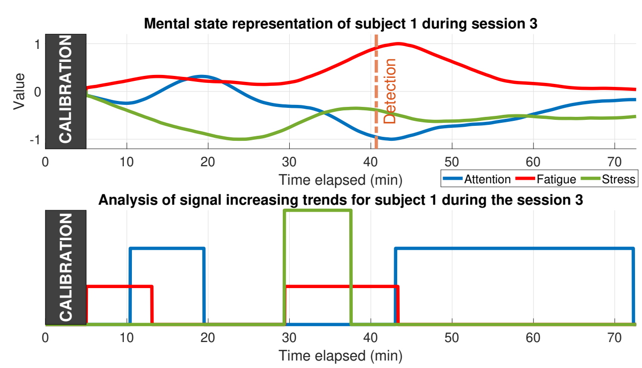


Fig. 1: Detection of the moment before low cognitive performance for subject 1 in the dataset 3 of Cao's experiment. **Top**: Representation of the mental states and the detection moment. The orange line represents the moment before poor cognitive performance levels, after criteria is met. The condition that has been met for detection is that both the mental state of fatigue and stress have remained with increasing trends over the time thresholds allowed: T_f and T_e and attention presented a decreasing trend. **Bottom**: Analysis of the mental state trends. These graphs represent the increasing moments of the mental states, where the values are constant when the signals have an increasing behavior or stay at zero in other cases.

III. Results

This section presents the analysis of the tendencies of the mental states of the subjects when carrying out the cognitive activities. The average duration for dataset 1 sessions was

78.5 $\pm$ 22.4 minutes, while dataset 2 sessions lasted 30, 20, and 30 minutes, respectively. Figure 2 displays the mental state representations for both datasets.

A. Dataset 1

The attention index displayed a decreasing trend during the first 5 minutes after calculating the baseline for all the users. In the next 12 minutes, this mental state presented a constant trend. For the rest of the duration of the recordings, it showed an increasing trend until reaching a peak, from which it decreases.

The fatigue index presented a positive slope during the first 10 minutes after calculating the baseline and remained constant for 5 minutes. In the following 15 minutes, it had a tendency to decrease until it reached a valley. For the final minutes, this mental state presented a growth trend.

For the stress index, during the first 15 minutes after the calibration procedure, it was observed that the graph presented a decreasing behaviour in the slope. For the next 5 minutes it started to grow until reaching a temporary peak and by the end, this mental state tended to grow.

B. Dataset 2

A very similar behaviour was observed in these sessions for each of the mental states when compared to the previous dataset during the first minutes. For the attention index, during the first 7 minutes after calculating the baseline, it showed a tendency to decrease until it reached a valley, from which it began to grow towards the end of the session.

For fatigue index, in the first 4 minutes of the session after the baseline, the signal presented a decreasing slope, and in the next minutes, it began to have a crescent shape before reaching a peak where it began to decrease again.

The stress index presented a decreasing trend, that was observed for the first 5 minutes after the calibration period, followed by minimal growth and decrease in trend until the end.

C. Detection of low cognitive performance periods

For dataset 1, the average detection of the moment before low cognitive performance happened at 35.3 $\pm$ 18.9 minutes and was detected in 80.6% of the sessions. For dataset 2, the detection times happened at 11.9, 12.3 and 8.3 minutes, respectively. These results are presented in Table I.

TABLE I: Summary of the low cognitive performance detection results

	Dataset 1	**Dataset 2**
Number of sessions	62	3
Number of subjects	27	2
Session length (min)	78.5 $\pm$ 22.4	30, 20, 30
Detection time (min)	35.3 $\pm$ 18.9	11.9, 12.3, 8.3
Low performance detections (%)	80.6	100

IV. DISCUSSION

In this study, a new method for detecting the previous moment of low cognitive performance is assessed based on the analysis of neurophysiological indices tendencies.

The results for the average detection time obtained for dataset 1 are consistent with those from previous studies, which could indicate that the average time a person can stay focused on a task they are familiar with is approximately 20 minutes. After this detection time, the person will not be able to continue with the activity and may need to take a break to recover. For dataset 2, the early detections could indicate subjects were not comfortable with the performed activity.

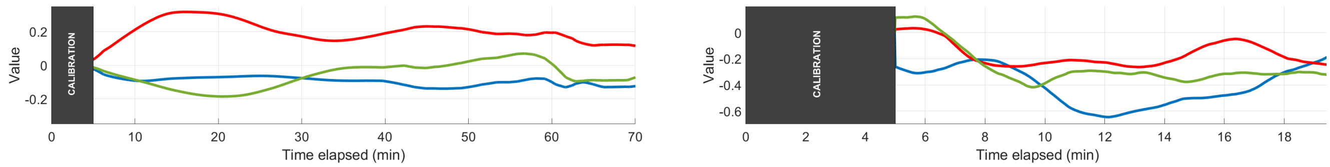
Regarding trends of the mental states, the analysis suggests the following: for attention index, the decreasing levels during the first minutes show that the person is not involved and motivated with the activity yet because the person is starting to focus. In the next minutes, the increase in the levels of attention evidence that the person begins to feel familiar and getting more involved. Subjects develop a greater affinity with the task and can perform optimally when they acquire a certain level of competence. However, it should be clarified that, although levels of attention may be high during this period, the manifestation of fatigue and stress may lead to believe that the person is making a greater cognitive effort to stay in tune with the task, and as a consequence affecting the overall performance. The signs of exhaustion accompanied by a decrease in the levels of attention suggest that prolonged cognitive activities carried out for long periods lead to a decrease in the performance of the task at hand.

For the fatigue index, the progressive increase at the beginning was expected, as subjects are not overloaded with information or exhausted initially or during a moment of engagement, but after some minutes it starts to increase due to the nature of these cognitive activities, supporting studies that have shown that fatigue tends to increase over time. The decrease during the middle and final period is related to the person feeling energized and perceiving the task as an easy activity, which is related to the increase in engagement and motivation.

For the stress index, the decreasing trend showed during the first minutes of the sessions may correspond to the person feeling relaxed and not motivated with the activity yet. This may correspond to the alarm phase, in which the person is warned of the situation but is not mentally exhausted yet. Throughout the middle stage, the increasing trend leads to believe that the person is motivated and focused on the task at hand, which may suggest that the stress levels are optimal. In the following moments, the appearance of stress at a medium level across subjects might suggest that the mind and body have run out of energy to cope with the task causing the subject to feel cognitively and physically affected. This fits the theory that, as the activity progresses, the performance is reduced, due to anxiety, fatigue and burnout.

FUTURE WORK

Future work involves evaluating more subjects to validate the detected trends for each of the mental states using the proposed neurophysiological indices and compare these results with post-session feedback. Different tasks' performance could also be analyzed using the proposed indices to determine whether the detection is possible.



(a) (b)

Fig. 2: Mental state average signals for the datasets evaluated. (a) Average mental state signal of the sixty-two sessions of Cao's experiment for the twenty-seven subjects. (b) Average mental state signal of the three sessions of the experiment with the g.Nautilus equipment for the two subjects.

Conclusion

In this paper, an approach to detect the early periods of low cognitive performance in sessions that require low physical activity based on the analysis of trends in neurophysiological indices, that characterize mental states, is proposed. The developed method stands out for its adaptability, as it can be used to evaluate different subjects without requiring training data, and understand the user's cognitive performance along the session. The neurophysiological indices and selected EEG channels to represent the mental states allow for reliable detection in most cases, which could evidence said indices' usefulness on understanding how mental states behave during this type of tasks and what conditions must be met to warn the subject about a moment of low cognitive performance.

Acknowledgement

The work presented in this paper was supported by Groupo de Investigación en Robótica Aplicada y Biomecánica (GIRAB) of Pontificia Universidad Católica del Perú (PUCP) for providing the equipment and facilities for the realization of the experiments.

Compliance with Ethical Standards

All procedures involving human participants were in accordance with the ethical principles outlined in the Helsinki Declaration of 1975, as revised in 2000. Additional informed consent was obtained from all subjects for which information is included in this article.

References

[1] Sarah Green Carmichael. The research is clear: Long hours backfire for people and for companies. *Harvard Business Review*, 19, 2015.

[2] Noa Herz, Shira Baror, and Moshe Bar. Overarching states of mind. *Trends in Cognitive Sciences*, 24(3):184–199, 2020.

[3] Laura Palmer. The relationship between stress, fatigue, and cognitive functioning. *College Student Journal*, 47(2):312–325, 2013.

[4] Michael J Connor. Making judgements about attention and concentration levels: How can we know what to expect? *Emotional and Behavioural Difficulties*, 2(2):14–20, 1997.

[5] Zizheng Guo, Ruiya Chen, Kan Zhang, Yirun Pan, and Jianhui Wu. The impairing effect of mental fatigue on visual sustained attention under monotonous multi-object visual attention task in long durations: an event-related potential based study. *PloS one*, 11(9):e0163360, 2016.

[6] Marian Joëls, Zhenwei Pu, Olof Wiegert, Melly S Oitzl, and Harm J Krugers. Learning under stress: how does it work? *Trends in cognitive sciences*, 10(4):152–158, 2006.

[7] Kristin Wong. How long it takes to get back on track after a distraction, 2015.

[8] Pierre Thiffault and Jacques Bergeron. Monotony of road environment and driver fatigue: a simulator study. *Accident Analysis & Prevention*, 35(3):381–391, 2003.

[9] Alan T Pope, Edward H Bogart, and Debbie S Bartolome. Biocybernetic system evaluates indices of operator engagement in automated task. *Biological psychology*, 40(1-2):187–195, 1995.

[10] Stefania Coelli, Roberta Sclocco, Riccardo Barbieri, Gianluigi Reni, Claudio Zucca, and Anna Maria Bianchi. Eeg-based index for engagement level monitoring during sustained attention. In *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 1512–1515. IEEE, 2015.

[11] Budi Thomas Jap, Sara Lal, Peter Fischer, and Evangelos Bekiaris. Using eeg spectral components to assess algorithms for detecting fatigue. *Expert Systems with Applications*, 36(2):2352–2359, 2009.

[12] Thien Nguyen, Sangtae Ahn, Hyojung Jang, Sung Chan Jun, and Jae Gwan Kim. Utilization of a combined eeg/nirs system to predict driver drowsiness. *Scientific reports*, 7:43933, 2017.

[13] Giorgos Giannakakis, Dimitris Grigoriadis, and Manolis Tsiknakis. Detection of stress/anxiety state from eeg features during video watching. In *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 6034–6037. IEEE, 2015.

[14] Richard S Lewis, Nicole Y Weekes, and Tracy H Wang. The effect of a naturalistic stressor on frontal eeg asymmetry, stress, and health. *Biological psychology*, 75(3):239–247, 2007.

[15] Tian Lan, Andre Adami, Deniz Erdogmus, and Misha Pavel. Estimating cognitive state using eeg signals. In *2005 13th European Signal Processing Conference*, pages 1–4. IEEE, 2005.

[16] John Atkinson and Daniel Campos. Improving bci-based emotion recognition by combining eeg feature selection and kernel classifiers. *Expert Systems with Applications*, 47:35–41, 2016.

[17] Zehong Cao, Chun-Hsiang Chuang, Jung-Kai King, and Chin-Teng Lin. Multi-channel eeg recordings during a sustained-attention driving task. *Scientific data*, 6(1):1–8, 2019.

[18] James W Bisley and Michael E Goldberg. Attention, intention, and priority in the parietal lobe. *Annual review of neuroscience*, 33:1–21, 2010.

[19] Maher Chaouachi and Claude Frasson. Exploring the relationship between learner eeg mental engagement and affect. In *International Conference on Intelligent Tutoring Systems*, pages 291–293. Springer, 2010.

[20] Adam R Clarke, Robert J Barry, Diana Karamacoska, and Stuart J Johnstone. The eeg theta/beta ratio: a marker of arousal or cognitive processing capacity? *Applied psychophysiology and biofeedback*, 44(2):123–129, 2019.

[21] Li-Wei Ko, Oleksii Komarov, W David Hairston, Tzyy-Ping Jung, and Chin-Teng Lin. Sustained attention in real classroom settings: An eeg study. *Frontiers in human neuroscience*, 11:388, 2017.

[22] Suvi Tiinanen, Antti Mättä, Minna Silfverhuth, Kalervo Suominen, Eira Jansson-Verkasalo, and Tapio Seppänen. Hrv and eeg based indicators of stress in children with asperger syndrome in audio-visual stimulus test. In *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 2021–2024. IEEE, 2011.