International Journal on Perceptive and Cognitive Computing (IJPCC) Vol 9, Issue 1 (2023)
https://doi.org/10.31436/ijpcc.v9i1.355

EEG Features for Driver's Mental Fatigue Detection: A Preliminary Work

Muhammad Afiq Ammar Kamaruzzaman, Marini Othman*, Raini Hassan, Abdul Wahab Abdul Rahman, NurHafizah Mahri

Kulliyyah of Information & Communication Technology, International Islamic University Malaysia

*Corresponding author: omarinii@iium.edu.my

(Received: 24th November 2022; Accepted: 10th January 2023; Published on-line: 28th January 2023)

Abstract— Mental fatigue is one of the most typical human infirmities, resulting from an overload of work and lack of sleep which can reduce one's intellectual resources. Different EEG features have been studied for detecting mental fatigue. This paper characterizes mental fatigue through the understanding of human EEG features for safe driving behaviour and to create an overview of the potential EEG features which are related to mental fatigue. A narrative review approach is employed for describing the neural activity of the human brain in mental fatigue. Specific EEG features in relation to driving tasks, relation to different EEG band waves, pre-processing and feature extraction methods are discussed. From this preliminary work, the increase of parietal alpha power seems to characterize the driver's mental fatigue in most of the studies. We searched public EEG repositories for identifying potential data sources for our initial study. Finally, we propose a conceptual model that has potentials for identifying mental weariness. In conclusion, future works may involve the identification of other EEG features of higher importance for generalization across study conditions.

Keywords— EEG sensor, psychological fatigue, driver's fatigue, traffic safety.

I. Introduction

Statistics from the World Health Organization (WHO) have revealed that 1.2 million people died as a result of traffic injuries [1], signifying a global public health issue. Past studies have indicated that human factors such as fatigue play a significant role in road accidents compared to other factors such as vehicle conditions and environmental factors. In a recent study, the physiological and psychological disorders related to fatigue were some of the factors that can lead to serious accidents as fatigue can affect on driver's vision, hearing, decision-making, and attention [2].

In the traffic safety literature, fatigue can be categorized into physical fatigue and mental fatigue. Physical and mental energy are governed by distinct underlying processes. Putting too much strain on one's muscles may cause physical fatigue [3], resulting in stiffness and tension in one's muscles [4, 5]. From another perspective, in high-intensity work out a person might be physically exhausted and struggle to run, lift, or play, but his alertness and concentration may still remain intact. In fact, most research concludes that physical activity has either a positive effect or more often, little or no impact on mental performance [6, 7]. On the contrary, mental fatigue may affect physical performance. Past studies have provided evidence that cognitive load in the human brain may reduce effectiveness in performing specific tasks and cause reduced attention [8, 9]. Hence it is more worthwhile to focus on mental fatigue rather than physical fatigue paragraph.

The analysis of brain signal activities through the electroencephalogram (EEG) may help to understand variations in the driver's performance. The advantages of using EEG for tracking driver's responses include high temporal resolution, the mobility of the EEG device and involves non-invasive recording. As a result of the said advantages, EEG is widely used for clinical and psychiatric research, such as studying sleep patterns, brain developmental disorders, and patients' cognitive states. Most recently, brain-computer interfaces and neuro-marketing are some of the emerging EEG applications researched around the world. These advancements are mainly triggered by the availability of appropriate EEG hardware and increased computing power for analyzing human EEG.

The next section of this paper defines and explains the symptoms of mental fatigue. It also describes the basic characteristics of the human EEG and how these data can be analyzed in the context of driving conditions. Following these analysis approaches, EEG features in relation to mental fatigue are reviewed. The paper concludes with consistent EEG patterns found among the studies.

II. Definition and Symptoms of Mental Fatigue

Mental fatigue is one of the most typical human infirmities, resulting from an overload of work and lack of

https://doi.org/10.31436/ijpcc.v9i1.355

sleep which can reduce one's intellectual resources. The terms "sleepiness", "drowsiness" and "tiredness" are perceived as symptoms of fatigue and are frequently used interchangeably in the traffic safety literature. Past researchers have documented numerous traffic casualties caused by mental fatigue. A survey of 9,200 accident-involved drivers in Norway found that 3.9% were sleep-related, but almost 20% of night-time accidents involved drivers' drowsiness [10]. "Tiredness" has been the main factor in 7.3% of accidents happening in the United Kingdom [11]. In a recent study, the physiological and psychological disorders related to fatigue were one of the factors that can lead to serious accidents as fatigue can effect on driver's vision, hearing, decision-making, and attention [2].

Over a span of cognitive activities will reduce the efficiency in cognitive performance, and such a psychobiological state is defined as mental fatigue [12]. A landmark study asserts that mental fatigue is a condition that emerged due to gradual and accumulative mental effort which can cause sleepiness, distraction, and poor concentration [3].

Mental fatigue also affects information processing in our brain and caused poor concentration, and lack of mental control, and even leads to decision or action errors [13,14,15]. As a result of poor actions and decision-making, a person suffering from mental fatigue experiences reduced motivation for completing a task, has a disturbance of thinking skills, and has a higher chance of negative emotions. These impairments are increasingly becoming a common phenomenon and have caused major accidents around the world [12]. Figure 1 summarizes the symptoms of mental fatigue.

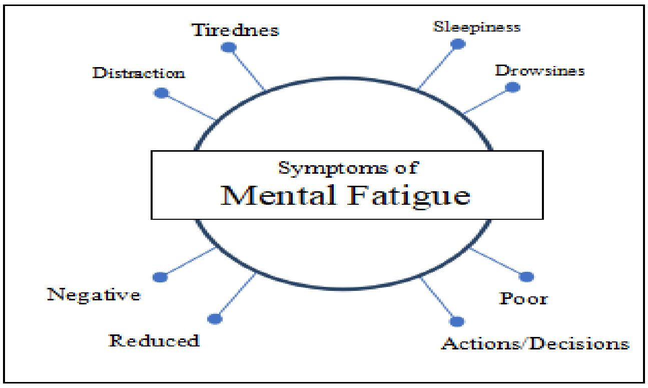

Fig. 1 Symptoms of mental fatigue

III. Electroencephalogram

An electroencephalogram is an established approach for detecting brain activities. EEG relies on the detection of the electrical activity of the human brain, as a result of the firing of neurons during cognitive states. The brain is located at the top part of an animate body, typically close to the sensory organs. There are roughly 15-33 billion neurons in the cerebral cortex [15], each of them connected by synapses to several thousand other neurons. These neurons communicate with one another by means of long protoplasmic fibers called axons, which carry trains of signal pulses called action potentials to distant parts of the brain or body targeting specific recipient cells.

The human brain is basically a complex structure that can connect and communicate with other bodily system such as the respiratory system, the nervous system, and the muscle system. These systems combine to form a larger structure of the human body. Essentially, the human brain holds an important key in the evaluation, coordinating, and controlling human behaviour [16].

Sanei and Chambers [17] literally described EEG as "the writing and drawing of electrical signals emitted from the human scalp". These signals can be captured by placing electrodes on the human scalp. A typical EEG recording can be recorded using various configurations of 16, 32, and 64 channels.

EEG signals can be characterized by rhythmic wave patterns, namely the alpha, beta, gamma, delta, theta, kappa, lambda, and mu wave. The most reliable and consistent in terms of occurrence have been alpha, beta, delta, and theta [18]. These wave patterns are characterized by a range of frequencies, with a diversity of EEG activities in a developing brain, in contrast to the adult brain (Table 1). Average adult EEG frequency typically stands at 10Hz while average infant frequency ranges between 3Hz to 7Hz [19].

TABLE I

EEG Wave Patterns

EEG wave patterns	**Frequencies (Hz)**	**Conditions**
Delta	0.5-4	Appear during deep sleep in normal adults
Theta	4-8	State of pleasure and displeasure Drowsiness in young adults Babies experiencing pleasurable events
Alpha	8-13	Relaxed state Produced by adults sitting quietly with eyes closed
Beta	14-30	Found in adults involved in mental and physical activities

The relationship between numerous cognitive states and the matching brain dynamic of a subject [10] can be understood by analyzing the human EEG. Depending on a driver's level of mental fatigue, reduced effectiveness of cognitive activities might be observed as the level of task difficulties are increased [2]. Consequently, the efficiency of

https://doi.org/10.31436/ijpcc.v9i1.355

analyzing information and decision making will somehow be decreased from prolonged usage of cognitive activity thus affecting drivers to sustained attention and visuals [14].

IV. Categories of Analysis in Mental Fatigue

Characteristics of the EEG in mental fatigue can be identified either using qualitative or quantitative methods. Qualitative EEG involves specific EEG measures known as the Event-Related Potentials (ERPs), activated following eliciting events through sensory or cognitive stimulus [20]. Traditionally, the ERP is visually inspected by a trained neurologist. More recent studies are assisted by computers for finer-grained ERP analyses. However, the need for a longer data sweep for noise averaging continues to be the main weakness in ERP analyses.

On the other hand, quantitative EEG (qEEG) uses a collection of computerized tools encompassing multiple mathematical and statistical algorithms to analyze EEG signals. Categories of qEEG analyses in mental fatigue include spectral analysis and functional connectivity analysis. Values and new patterns discovered through qEEG are collectively termed as "EEG features".

Functional connectivity analysis investigates the relationship of EEG signals in distinct brain regions. These relationships are quantified as some measures of synchronization between multiple regions [21]. Some of the measures include statistical approaches such as using the clustering coefficient and coherence analysis [22].

Spectral analysis is the most common method of analysis that involves the decomposition of EEG time series into the frequency domain, giving the spectrum of the EEG signals. It typically requires the application of Fourier Transform (FT) to yield the associated frequency bands as described in Section 3 above. The key idea of an FT is that a complex function such as observed in the raw EEG signals can be represented by a sum of general functions [23]. The spectral power can be calculated for each sub-band at each sensor. A total power value may also be computed over all sensors, giving a single power value for each frequency band. Thus, the power in the alpha band at each sensor location or the power for the alpha band for the entire scalp can be reported [21]. In addition, results may also be presented as absolute power or relative power. Relative power can be defined as the ratio of band power in a frequency band over all bands. Later, in some of the studies, machine learning algorithms were further applied for investigating causal relationships between the extracted features and EEG observations.

V. EEG Features in Mental Fatigue Detection

In [22], brain signals were acquired using a 64-channels, standardized using 10-20 International system. Initially, electrode impedance in the EEG was set up below 10kΩ and during the sampling rate was 512Hz. The signal was downsampled from 512 Hz to 256 Hz for shorter processing time without significant loss of necessary information. FIR filter was used for filtering the band-pass between 1 to 40 Hz. Later, weighted connectivity matrix was constructed using Phase Lag Index (PLI). Analyses results indicated that the connectivity network construct will be too complex for meaningful biomarkers to be observed and the graph theory seems to be the best approach for the network [22].

In another experiment designed to detect mental fatigue [26], EEG signals were measured using 64 channels based on the 10-20 International system. A sampling rate of 512 Hz was used for this experiment and 10 K electrode impedances were maintained in all the trials. From 512Hz the signal of EEG was down sampled to 256Hz. Filtering was performed using an FIR filter and a cut-off bandpass frequency of 1 to 40Hz. The filtered data were extracted for the frequency bands of the delta, theta, alpha, beta, and lower gamma by means of FFT. Meanwhile, for the regression process, Random Forest (RF) was used to gauge the strength of each feature in relation to fatigue.

In [25], EEG signals were measured using 26-channels Quick cap following the standardized positions of FP1, FP2, F7, F3, Fz, F4, F8, FC3, FCz, FC4, T3, C3, Cz, C4, T4, CP3, CPz, CP4, T5, P3, Pz, P4, T6, O1, Oz, and O2. The reference was the average of A1 and A2 while the sampling frequency was 500Hz. Principal Component Analysis (PCA) was used as the filter to reduce data dimensionality. EEG features were extracted using power spectral density (PSD) and reported based on EEG frequency bands of the delta, theta, alpha, and beta. The calculation of the PSD value was based on the trapezoidal rule of numerical integration.

In [27], a portable 16-channels with a USB amp signal amplifier was used in the research study. For the signal acquisition, 24-bit quantification with active electrodes was used and the sampling rate was 256Hz. The electrode placement on the head scalp is based on 10-20 international electrode placements of O1, O2, P3, P4, P7, P8, OZ, FP1, FP2, CZ, FZ, T7, and T8. A2 was used as a reference electrode meanwhile Fz for ground electrode. The EEG signal was first processed by executing a bandpass filter between 0.5 and 60 Hz. Then, the signal was notch filtered to remove the AC power frequency. For the feature extraction, Power Spectral Density (PSD) and Fast Fourier Transform (FFT) analyzing techniques to determine the absolute and relative powers of the alpha frequency band [27].

A related study from [2] used the Emotiv Epoc headset with a sampling frequency of 128 Hz. Fourteen channels of EEG from AF3, F7, F3, FCS, T7, P7, 01, 02, P8, T8, FC6, F4, F8, and AF4 were recorded. Integrate pre-processing was

https://doi.org/10.31436/ijpcc.v9i1.355

utilized for de-noising followed by a Butterworth LP filer to remove power line interference. Later, a wavelet analysis took place where 7 layers of demy wavelet were used to determine the de-noising threshold. For EEG features extraction a rhythm wave extraction was used based on wavelet packet transform.

In [28], 32-channels of EEG were used for signal recording with a sampling rate of 2048Hz. Pre-processing was done by resampling the signal to 256Hz. The analysis was focused on 12 channels only (F3, F4, Fz, C3, C4, Cz, P3, P4, Pz, 01, 02, and Oz) which covers the left, right, midline, frontal, central, parietal and occipital cortical scalp regions. Pre-processing was performed with a high pass filter applied at 1 Hz to remove movement artifacts. For feature extraction, S-transform which is a combination of Short Time Fourier Transform (STFT) and wavelet transform [28] was used in the analysis.

Finally, in [24], the subject's mental fatigue was recorded using EEG BrainAMP system with 32 channels. EEG recorded signals were down sampled to 500Hz and referenced to Acticap. Common average reference was used for this experiment to filter the bandpass which is between 1 to 40Hz using Common Spatial Patter (CSP) filter. Welch's power spectral density estimation was used to estimate the average power in EEG signal related to five frequency bands which is the delta (1-4Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–40 Hz).

TABLE II
FINDINGS RELATED TO EEG FEATURES IN MENTAL FATIGUE DETECTION

Author (year)	**Findings**
Chua, et. al. (2017) [22]	Notably, the statistically different regions (p-value < 0.05) that showed a high correlation to fatigue were Fz, F2, C5, P2, P3, Pz, POz, 01, Oz and O2 (with a correlation p-value ≤ 0.01). Significant increase in clustering coefficient were found in the parietal and occipital area of the brain.
Dimitrakopoulos, et. al. (2017) [26]	Regression with RF on multiband power features was performed providing a highly accurate fatigue index
Chai, et. al. (2016) [25]	The classification result of this study validates the use of the PCA-BNN for pre-task as fatigue data vs. post task (alert) classification with an accuracy around 75%, which involved series eight mental load tasks.
Gharagozlou, et. al. (2015) [27]	Significant increase in the absolute alpha power (P = 0.006) as well as F-VAS scores during the final section of driving (P = 0.001).
Wang, et. al. (2015) [2]	An increased degree of fatigue causes an increase in delta rhythm relative energy, while sampling entropy and alpha rhythm relative energy decrease. A combination of relative energy and sample entropy can improve the accuracy of classification.
Tran, et. al. (2014) [28]	Mental fatigue is associated with increases in maximum alpha activity (Amaxα(t)) and increases in the sum of alpha amplitude (Asumα(t)). The increases were observed across the cortex, and found to be significant in the Cz and P4 sites (p<0.05).
Roy, et. al. (2013) [24]	The lower alpha frequency band increased with growing Time-On-Task for all midline electrodes (p<0.05)

VI. EEG DATASETS RELATED TO MENTAL FATIGUE

At the point of our research, we could not retrieve any public EEG dataset specifically related to EEG and driver's mental fatigue. We searched 3 data repositories, namely Kaggle, UCI Machine Learning and Physiobank. An initial keyword search "(mental fatigue) and (eeg or brain signal)" was unsuccessful. Based on the works of Petticrew and Roberts [28], the keywords were simplified to "mental fatigue" for increasing the proportion of the outcomes. Three datasets from Kaggle were retrieved as the results of the updated keywords, while none were returned from UCI Machine Learning and Physiobank. Upon further investigation on the 3 datasets, we found that none of these are consist of EEG data nor driving scenarios (Table IV). However, from the dataset descriptions, related keywords that are worth future investigations are "burnout" and "resource allocation".

TABLE III
SYSTEMATIC SEARCH ON PUBLIC DATASETS

Data repository	**Keywords search**	**No of results**
Kaggle	(mental fatigue) and (eeg or brain signal)	0
	mental fatigue	3
UCI Machine Learning	(mental fatigue) and (eeg or brain signal)	0
	mental fatigue	
Physiobank	(mental fatigue) and (eeg or brain signal)	0
	mental fatigue	

https://doi.org/10.31436/ijpcc.v9i1.355

TABLE IV
DATASETS RELATED TO MENTAL FATIGUE

Author (year)	Dataset descriptions	Type of data
HackerEarth (2020) [29]	Employees burnout during Covid-19	Psychometric questionaires and scales
No author [30]	Mental fatigue, resource allocation, employee burnout	Psychometric questionnaires and scales
Allen, J. (2021) [31]	Covid-19 data	Psychometric questionnaires and scales

VII. CONCEPT

Figure 2 depicts the conceptual model for our research based on our preliminary findings. Data acquisition will be carried out using 19-channels DABO EEG machine in different driving scenarios. In the EEG pre-processing we apply artifact rejection to remove eyes and muscle movements. Next, we apply a bandpass filter for obtaining varying frequencies of the EEG signals, namely delta, theta, alpha, beta and gamma bands. In the feature extraction stage, we perform signal averaging for retrieving the Event-Related Potentials (ERP). These features will be subjected to binary logistic regression and SVM classification for yielding either mental fatigue or non-mental fatigue conditions.

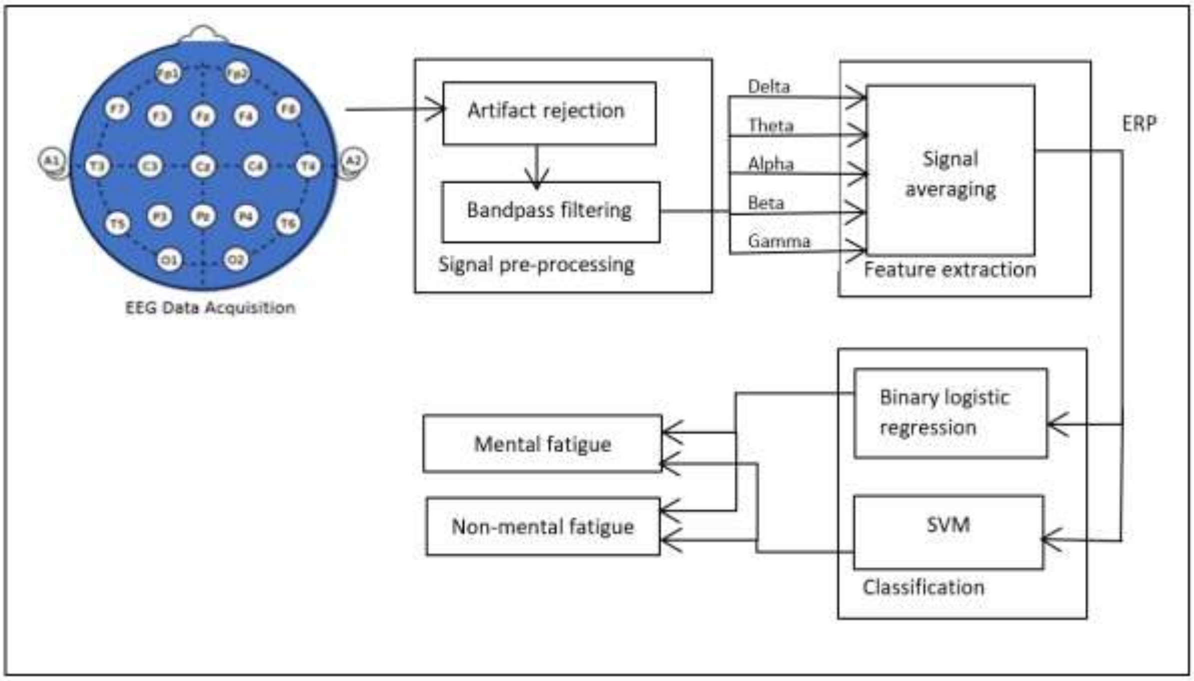

Fig. 2 Conceptual model for detection of mental fatigue

VIII. CONCLUSIONS

In the reviewed studies, EEG spectral analysis seems to be the most popular measure for EEG drivers' mental fatigue detection. The most consistent findings can be found in the increase of alpha power or relative power, specifically in the parietal regions. Spectral analysis is easy to compute and interpret even with a single sensor. However, generalization must be approached with care since different study conditions might affect changes in the alpha band. In the context of functional connectivity, the relationship between different network regions and the observed signal of a fatigued brain is hard to establish since only a single study was discussed in this review. However, like spectral analysis, it is interesting to note that the functional connectivity analysis also yields the parietal region as worthwhile to be further investigated.

Additionally, we search 3 public EEG repositories and found that all the retrieved datasets were consists of psychometric questionnaires and scales. As such the proposed conceptual model include EEG data acquisition from human subjects, that shall include differing driving tasks and conditions. Signal pre-processing, feature extraction and binary classifications were proposed for obtaining the conditions of mental fatigue and non-mental fatigue conditions.

In conclusion, the reviewed studies give interesting insights into understanding the brain's cognitive activities by identifying specific EEG features in relation to mental fatigue. There were some patterns found specifically in the parietal alpha, although generalizations cannot be drawn yet due to technical difficulties such as a distinct study design employed within limited sample sizes. Also, most of the studies do not indicate the use of medications that may affect their EEG features. A wide range of analysis methods suggested the high utility of human EEG in detecting drivers' mental fatigue. The current literature suggested that more EEG features of higher importance need to be investigated. New analysis methods may contribute towards a new EEG-based mental fatigue indicator that assists drivers in decision-making and eventually reduce traffic casualties.

ACKNOWLEDGEMENT

The authors would like to thank the Kulliyyah of Information and Communication Technology (KICT), International Islamic University Malaysia (IIUM) for providing financial support through the KICT Research Initiative Grant (Project KICT-RG20-007-0007).

CONFLICT OF INTEREST

The authors declare that there is no conflict of Interest

REFERENCES

[1] World Health Organization. Global status report on road safety 2015. World Health Organization.
[2] F. Wang, J. Lin, W. Wang & H. Wang. EEG-based mental fatigue assessment during driving by using sample entropy and rhythm energy. In Cyber Technology in Automation, Control, and Intelligent Systems (CYBER), 2015 IEEE International Conference on (pp. 1906-1911). IEEE, 2015.
[3] E. Grandjean. Fatigue in industry. Occupational and Environmental Medicine 36(3), 175-186, 1979.
[4] W. Hu, K. Li, N. Wei, S. Yue, & C. Yin. (2017, October). Influence of exercise-induced local muscle fatigue on the thumb and index finger forces during precision pinch. In Chinese Automation Congress (CAC), 2258-2261, IEEE, 2017.
[5] K., Kourakata & Hotta, Y. Muscle fatigue detection during dynamic contraction under blood flow restriction: Improvement of detection sensitivity using multivariable fatigue indices. In Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE, pp. 6078-6081, IEEE, 2015.
[6] G. C. Bogdanis. Effects of physical activity and inactivity on muscle fatigue. Frontiers in physiology, 3(142), 2012.
[7] A. S. Krausman, H. P., Crowell III, & R. M. Wilson. The effects of physical exertion on cognitive performance (No. ARL-TR-2844), 2002.
[8] B. Chakraborty, & K. Nakano. Automatic detection of driver's awareness with cognitive task from driving behavior. In Systems, Man, and Cybernetics (SMC), 2016 IEEE International Conference on, pp. 003630-003633, IEEE, 2016.
[9] S. Sarkar, & C. Parnin. (2017, May). Characterizing and predicting mental fatigue during programming tasks. In Proceedings of the 2nd International Workshop on Emotion Awareness in Software Engineering, pp. 32-37, IEEE Press, 2017.
[10] F. Sagberg. (1999). Road Accidents Caused by Drivers Falling Asleep, Accident Analysis and Prevention, 31(6), 1999.
[11] G. Maycock. Driver Sleepiness as a Factor in Car and HGV Accidents, Transport Research Laboratory (TRL), Crowthorne, Berkshire, UK, New South Wales Road Safety Bureau RUS No 5, 1995.
[12] M. Tanaka, A. Ishii & Y. Watanabe. Neural effects of mental fatigue caused by continuous attention load: a magnetoencephalography study. Brain research, 1561, pp. 60-66, 2014.
[13] S. Yang, Y. Qiao, L. Wang, & G. Xu. Effect of magnetic stimulation at acupoint on event related potential MMN during mental fatigue, 2015 IET International Conference on Biomedical Image and Signal Processing (ICBISP 2015), Beijing, pp. 1-4, 2015.
[14] Z. Guo, R. Chen, K. Zhang, Y. Pan, & J. 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), 2016.
[15] D. P. Pelvig, H. Pakkenberg, A. K. Stark, & B. Pakkenberg. Neocortical glial cell numbers in human brains. Neurobiology of aging, 29(11), 1754-1762, 2008.
[16] J. J. J. Davis, C. T. Lin, G. Gillett, & R. Kozma. An Integrative Approach to Analyze Eeg Signals and Human Brain Dynamics in Different Cognitive States. Journal of Artificial Intelligence and Soft Computing Research, 7(4), 287-299, 2017.
[17] S. Sanei & J. A. Chambers. EEG signal processing, John Wiley & Sons Ltd, 2007.
[18] J. L. Andreassi. Psychophysiology: Human behavior and psychological response,New York, NY, Psychology Press, 2007.
[19] M. A. Bell, and C. D. Wolfe. The Use of the Electroencephalogram in Research on Cognitive Development. In L. A. Schmidt & S. J. Segalowitz (Eds.). Developmental Psychophysiology: Theory, Systems, and Methods (pp. 150-172). Cambridge: Cambridge University Press, 2008.
[20] J. Yordanova, & V. Kolev. (2009). Event-related brain oscillations: Developmental effects on power and synchronization. Journal of Psychophysiology, 23(4), 174, 2009.
[21] O. Gurau, W. J. Bosl, & C. R. Newton. How Useful Is Electroencephalography in the Diagnosis of Autism Spectrum Disorders and the Delineation of Subtypes: A Systematic Review. Frontiers in psychiatry, 8, pp. 121, 2017.
[22] B. L. Chua, Z. Dai, N. Thakor, A. Bezerianos, & Y. Sun. Connectome pattern alterations with increment of mental fatigue in one-hour driving simulation. In Engineering in Medicine and Biology Society (EMBC), 2017 39th Annual International Conference of the IEEE (pp. 4355-4358). IEEE, 2017.
[23] E. M. Stein, & R. Shakarchi. Fourier analysis: an introduction (Vol. 1). Princeton University Press, 2011.
[24] R. N. Roy, S. Bonnet, S. Charbonnier, & A. Campagne. Mental fatigue and working memory load estimation: interaction and implications for EEG-based passive BCI. In Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE (pp. 6607-6610). IEEE, 2013.
[25] R. Chai, Y. Tran, G. R. Naik, T. N. Nguyen, S. H. Ling, A. Craig & H. T. Nguyen. Classification of EEG based-mental fatigue using principal component analysis and Bayesian neural network. In Engineering in Medicine and Biology Society (EMBC), 2016 IEEE 38th Annual International Conference of the (pp. 4654-4657). IEEE, 2016.
[26] G. N. Dimitrakopoulos, I. Kakkos, N. V. Thakor, A. Bezerianos, & Y. Sun. A mental fatigue index based on regression using mulitband EEG features with application in simulated driving. In Engineering in Medicine and Biology Society (EMBC), 2017 39th Annual International Conference of the IEEE (pp. 3220-3223). IEEE, 2017.
[27] F. Gharagozlou, G.N. Saraji, A. Mazloumi, A. Nahvi, A.M. Nasrabadi, A. R. Foroushani & M. Samavati. Detecting driver mental fatigue based on EEG alpha power changes during simulated driving. Iranian Journal of Public Health, 44(12), 1693, 2015.

https://doi.org/10.31436/ijpcc.v9i1.355

[28] Y. Tran, R. Thuraisingham, N. Wijesuriya, A. Craig, & H. Nguyen. Using S-transform in EEG analysis for measuring an alert versus mental fatigue state. In Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE (pp. 5880-5883). IEEE, 2014.

[29] M. Petticrew, & H. Roberts. Systematic Review in the Social Sciences: A Practical Guide. John Wiley & Sons, 2008.

[30] HackerEarth. Are Your Employees Burning Out? [Data set]. Kaggle, 2020. Retrieved 22 January 2023 from https://doi.org/10.34740/KAGGLE/DS/949779

[31] n.d. B1Dataset [Data set]. Kaggle, 2021. Retrieved 22 January 2023 from https://www.kaggle.com/datasets/viratkothari/b1dataset

[32] J. Allen. Covid-19 data [Data set]. Kaggle, 2021. Retrieved 22 January 2023 from https://www.kaggle.com/datasets/anushabellam/covid-19-newyork-dataset