Mental Workload Assessment using Low-Channel Prefrontal EEG Signals

1st Matin Beiramvand
Tampere University
Pori, Finland
matin.beiramvand@tuni.fi

2nd Tarmo Lipping
Tampere University
Pori, Finland
tarmo.lipping@tuni.fi

3rd Nina Karttunen
Satakunta University of Applied Sciences
Pori, Finland
nina.j.karttunen@samk.fi

4th Reijo Koivula
Tampere University
Pori, Finland
reijo.koivula@tuni.fi

***Abstract*—*Objective*: Monitoring stress using physiological signals has recently achieved a lot of attention since it has a significant adverse influence on an individual daily's health and efficiency. As it has been proven that stress and mental workload are proportionally correlated, several studies have proposed algorithms for stress monitoring by increasing the mental workload. Despite the promising results reported in the literature, a majority of the proposed algorithms require the employment of several physiological signals which hinder their real-life application. Nonetheless, the advent of low-cost wearable devices has provided a new possibility for outdoor stress monitoring. The objective of this paper is to present an algorithm for stress detection using low-channel prefrontal electroencephalography (EEG) data. *Methods*: Firstly, artifacts in EEG signals are removed. Secondly, EEG signals are split into sub-bands using the discrete wavelet transform and two nonlinear parameter-free features are extracted. Thirdly, the extracted features are fed to three classifiers, i.e., support vector machine, Adaboost, and the K-Nearest Neighbours to discriminate stress from relaxed states. *Main results*: According to the obtained results, the highest accuracy (80.24%) was achieved using the AdaBoost classifier. *Significance*:Given that the proposed method does not require any parameter adjustment before processing, it has the potential to be used in real-world scenarios.**

***Index Terms*—Cognitive load, Stress, EEG, Wearable, Nonlinear feature**

I. Introduction

Cognitive load refers to the amount of mental effort or resources required to perform a task or set of tasks. Mental stress, on the other hand, is the emotional and psychological response to certain triggers or events. There is a relationship between cognitive load and mental stress in that high levels of cognitive load can contribute to the experience of mental stress. When the cognitive load exceeds a person's capacity to handle it, it can lead to difficulty in completing tasks, which can contribute to mental stress [1]. Additionally, mental stress can also increase cognitive load, as it can make it difficult to focus and can lead to decreased cognitive performance. Therefore, cognitive load and mental stress are closely related since they can both negatively affect one another [2]. However, it is important to note that stress can also be caused by a variety of other factors. The high cognitive load can be just one of many contributing factors to the development of stress. Generally, there are two main modalities that are being used for mental stress and cognitive load detection: subjective and physiological. The subjective approaches such as self-report questionnaires (PSS) are prone to bias due to individualistic feedback [3]. The physiological approach comprises biomarkers from heart, brain, and blood volume [4], which have been proven more promising for the accurate detection of stress. Nevertheless, as stress is a mental phenomenon, analyzing the electrical activity of the brain can be a better option compared to other measurements [4]. Amongst the neuroimaging methods, Electroencephalogram (EEG) has been proven as the most effective technique as it provides excellent temporal resolution [5]. In particular, the advent of low-cost EEG headbands provides a new possibility for stress and cognitive load detection outside the laboratory, which is of great importance in reducing the cost for the consumer and save time for medical doctors. Therefore, several studies have considered cognitive load detection using such systems.

Saeed et.al. [6] used a single-channel EEG headset to quantify human stress with eyes closed. Beta waves were used to predict the PSS score of an individual by a regression method, but there was no information regarding the subject's mental state during the EEG recording. In [7], a low-channel model of wearable EEG sensors for detecting chronic stress and low cognitive load was designed. The proposed model consists of a novel idea to assess the quality of EEG, applying a combination of linear and nonlinear features. The obtained results showed significant difference in the power asymmetry of Alpha, Beta, and Theta bands between individuals experiencing stress and normal controls. In [8], four EEG channels at the Prefrontal Cortex (PFC) area were targeted for the classification of stress and an accuracy of 50 % was reported. After adding more physiological signals, the accuracy increased to 85 %. In another study, the combination of a single channel EEG, Heart Rate Variability (HRV), and Galvanic Skin Response (GSR) information from 15 subjects were studied and an accuracy of 86 % was obtained by the Support Vector Machine (SVM) classifier [9]. Another research [10] proposed low beta analysis to quantify stress and achieved an accuracy of 71.4 %. A combination of selected neural oscillatory features extracted from a single frontal EEG and PSS score was used for classifying stress [11] and the best result of 78.57 % accuracy was obtained using the SVM.

Although the reported results of the aforementioned studies

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are promising, they are prone to using several physiological variables and having low accuracy. In addition, the short period of data recordings used in the studies may make the reported results unreliable. This paper, therefore, presents a new method for the classification of cognitive load and stress using two prefrontal EEG channels. The hypothesis of the paper is that during cognitive load EEG signals show higher complexity and therefore, using nonlinear measures such as entropy can offer a better option compared to standard linear features. Yet, nonlinear measures usually require parameter tuning which is a laborious task. Hence, we propose Wavelet Log Entropy and Shannon Entropy which are parameter-free.

II. Data

In this work, the correlation between cognitive load and EEG features was studied to recognize the level of mental cognitive load. The n-back memory game was adopted as a proper test setting to elicit various levels of cognitive load [14]. The game is described briefly in subsection A, and the details of the examination setup and procedure are explained in subsection B.

A. N-back memory game

The n-back memory game [12] has been extensively used in cognitive studies [13], particularly those focused on working memory performance [14]. It consists of sequential stimuli such as alphanumeric characters shown on the screen or a series of auditory probes, as well as the ability to recall them afterward. During the game, the subject is asked to respond, for example, by a left click, if the previous stimulus presented was what is currently shown on the screen. The version of the n-back memory game utilized in this examination used simple visual stimuli as single digits (0-9) displayed on the laptop screen every 3 seconds. The target digit was supposed to be clarified by the subject by clicking the mouse. Gaming sessions contained 9 games starting with 2-back and going ahead randomly with varying levels ranging from 0-back to 2-back, with a brief break between the levels. Each level from 0 to 2 occurred 3 times and each game took 90 seconds. At level 0, the subject is instructed to left-click if the predefined target number is displayed on the screen. At level 1, the subject should left-click if the previous number appears on the screen, and at level 2 if the number occurring two steps earlier are displayed. In this experiment, cognitive load is rated into three levels (no load, medium, and high) and each level of the n-back game corresponds to one of these levels. For binary classification, we consider levels 1 and 2 as causing cognitive load and level 0 as the no-load state. All game events and details during every session, for instance: n-back game level changes, displayed digits, and mouse clicks, were stored in a log file.

B. Subjects and data

In total, 15 subjects were recruited between the ages of 18 and 65. There was no history of mental illness reported by any of the subjects. Students and staff at Tampere University, along with students and staff from Satakunta University of Applied Sciences, performed the EEG measurements used in this experiment in 2022. The study was approved by the Ethical Committee of Satakunta universities.

The setup for the test comprised a laptop, an n-back memory game, the Neuroelectrics® Instrument Controller (NIC2) software running on the laptop, and the ENOBIO® EEG recording system by Neuroelectrics® [15]. The ENOBIO system possesses a wireless connection between the EEG amplifier, attached to the electrode cap, and the laptop.

The version of the measurement equipment that was utilized in the test supported up to 20 channels, however, we used 7 channels for recording EEG. In view of the proposed algorithm being designed for commercial headbands, the two channels in the prefrontal area (Fp1 and Fp2) were only considered. EEG signals were recorded using Ag/AgCl electrodes located according to the international 10-20 system with sampling rate of 500 Hz.

C. Data segmentation

Due to the 90-second duration of each game, we separated the signals of each game into three parts. Therefore, each part of the EEG is 30 seconds long, giving us the opportunity to triple our database size. The 30s signal is divided into 10s subsegments for preprocessing.

III. Methods

A block diagram of the proposed algorithm can be found in Fig 1. Detailed explanations of the proposed algorithm can be found in the subsections below.

A. Data Acquisition and Preprocessing

Preprocessing of the EEG data was carried out using a standard pipeline that included zero-phase Butterworth band-pass filtering (0.5-40 Hz) and eye blink removal with Discrete Wavelet Transform (DWT) (see Fig. 2). Analogously to previous studies [16] and [17], db4 was used as the mother wavelet as there is a resemblance between db4 morphology and eye blinks.

B. EEG sub-bands extraction

The DWT is used to extract EEG sub-bands, which is one of its main applications [5]. Firstly, approximation $a_1[n]$ and detail $d_1[n]$ components are derived from the input EEG signal. Then, DWT decomposes $a_1[n]$ into another approximation $a_2[n]$ and detail $d_2[n]$ components. This decomposition procedure is continued up to the maximum DWT level L (see Fig. 3). The original EEG signal can be reconstructed from the components by:

$$x[n] = \sum_{l=1}^{L} d_l[n] + a_L[n], \tag{1}$$

In order to calculate the frequency band of each approximation and detail component, the following formula is used:

$$a_l = \left[0, \frac{Fs}{2^{l+1}}\right], d_l = \left[\frac{Fs}{2^{l+1}}, \frac{Fs}{2^l}\right], \tag{2}$$

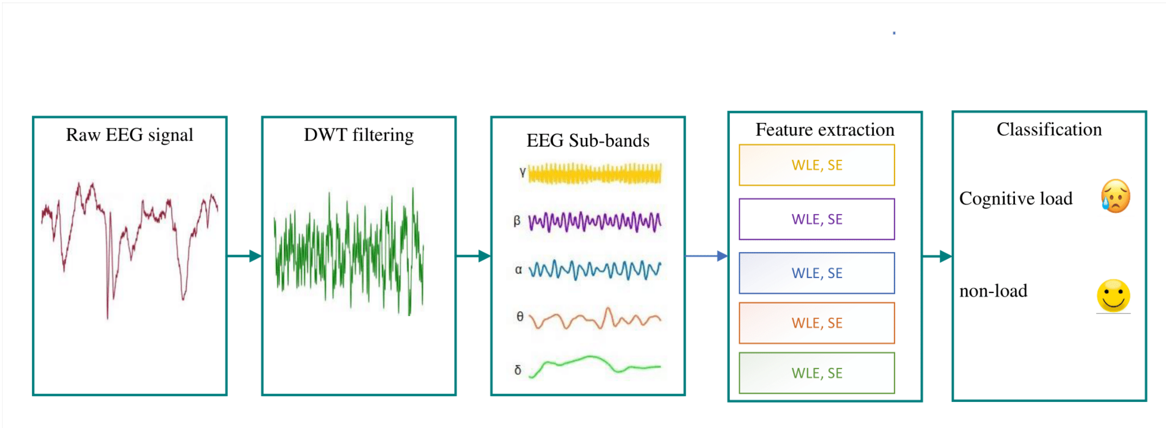

Fig. 1. Block diagram of the proposed algorithm for detecting cognitive load using the feature set applied to two prefrontal EEG channels.

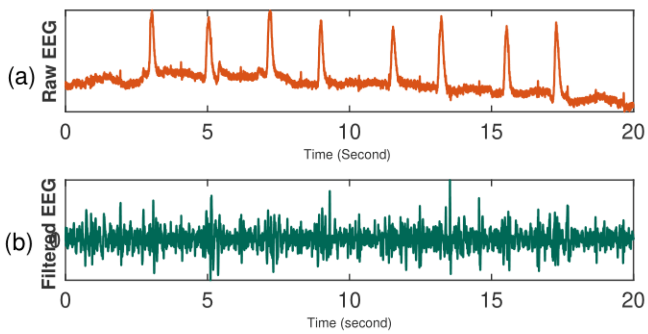

Fig. 2. An example of artifactual EEG and filtered EEG. a) An artifactual EEG contaminated with eye blinks and EMG. b) Noise-free EEG after applying filters

where L is the highest decomposition level. Considering the sampling rate of the EEG data and Equations 1 and 2, six levels of DWT can extract EEG sub-bands, where detail components of the third, fourth, fifth, and sixth levels correspond to gamma (25-40 Hz), beta (13-30 Hz), alpha (8-12 Hz), and theta (4-8 Hz) frequency bands, respectively, and the sixth level of approximation component relates to the delta (0-4 Hz) band.

C. Feature extraction and classification

After splitting the EEG into its sub-bands, Wavelet-Log-Entropy (WLE) and Shannon entropy (SE) are calculated from each sub-band [18] [19].

By employing symbolic dynamics, the Shannon entropy(SE) quantifies the signal's randomness as follows:

$$\mathrm{SE} = -\sum_{i=1}^{K} p(B_i) \times log(p(B_i)), \tag{3}$$

Where $p(B_i)$ is the probability of obtaining the value of B_i and B_i is the EEG band. WLE measure built on wavelet analysis can signify the complexity of unsteady signal defining as follows:

$$\mathrm{WLE} = \sum_{n} \log(B[n]^2), \tag{4}$$

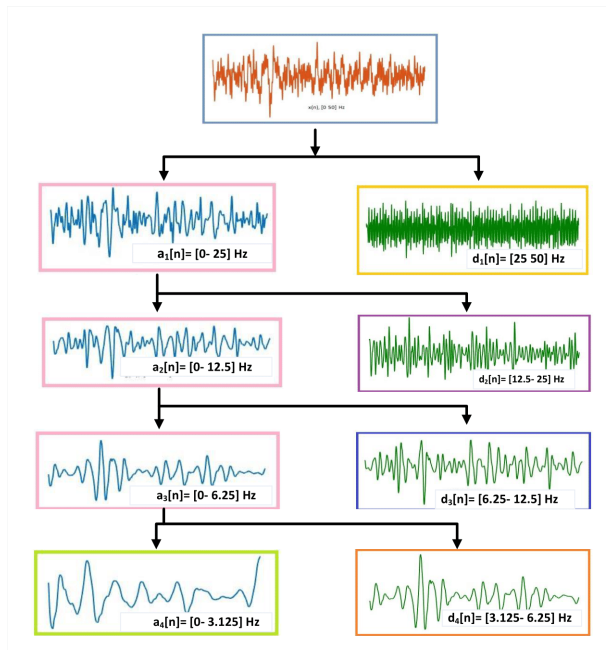

Fig. 3. An example of decomposed EEG signal into its sub-bands by DWT.

where $B[n]$ is the EEG band.

Therefore, the feature vector consists of 10 measures per channel. Then, the extracted features are normalized based on the z-score technique. Afterward, the data are randomly split into 70 % for training and validation, and 30% for testing purposes. To ensure the validity of the results, the training-validation procedure is executed based on 10-fold cross-validation, while the testing procedure is only conducted on data that has not been seen before. In this paper, we use the Support Vector Machine (SVM) with radial basis function kernel, Adaboost, and the k-Nearest Neighbour (kNN) methods to classify the EEG data into two classes, one corresponding to cognitive load and the other corresponding to the no-load state. It should be noted that the MATLAB 'Optimize Hyperparameters' function is used to optimize the hyperparameters during the training-validation phase based on the Bayesian optimization method.

To evaluate the classification results, the following formulas were used to calculate the Positive Predictive Value (PPV), Negative Predictive Value (NPV), Accuracy (Acc), Sensitivity (Sen), Specificity (Spe), and Area Under the Curve (AUC):

$$Acc = \frac{T_P + T_N}{T_P + T_N + F_N + F_P} \times 100, \quad (5)$$

$$PPV = \frac{T_P}{T_P + F_P} \times 100, \quad (6)$$

$$NPV = \frac{T_N}{T_N + F_N} \times 100, \quad (7)$$

$$\text{Sen} = \frac{T_P}{T_P + F_N} \times 100, \quad (8)$$

$$\text{Spe} = \frac{T_N}{T_N + F_P} \times 100, \quad (9)$$

$$\text{AUC} = \int \text{Sen}(T)(\text{1-Spe})'(T)dT, \quad (10)$$

where TP and FN represent the number of correctly and wrongly classified cases of high cognitive load (game levels 1 or 2), respectively, while TN and FP stand for the number of correctly and wrongly classified cases of no cognitive load (game level 0).

IV. Results

A. *Single feature classification*

Table I displays the classification results for the WLE and SE features in terms of validation and test data. As it is shown, the best classification results for the test dataset were obtained by the WLE as the feature and the AdaBoost as the classifier with an average Acc of 80.86%, PPV of 81.08%, and NPV of 80.80%. The boxplots of the feature values for each sub-band using single features are shown in Fig. 4. It can be seen that the entropy of the EEG tends to decrease in case of cognitive load in the Theta band while the opposite behavior can be seen in the Alpha band.

TABLE I
THE AVERAGE CLASSIFICATION RESULTS FOR VALIDATION AND TEST DATA.

		Validation data			Test data		
	Classifier	Acc	PPV	NPV	Acc	PPV	NPV
WLE	SVM	86.77	91.30	85.31	75.92	75.86	75.93
	kNN	83.33	76.92	86.20	75.92	69.23	78.04
	AdaBoost	**89.94**	90.74	89.62	**80.86**	81.08	80.80
SE	SVM	87.83	93.47	86.01	75.30	73.33	75.75
	kNN	82.80	75.63	86.10	75.30	68.42	77.41
	AdaBoost	**91.97**	89.25	92.99	**78.39**	75.67	78.20

B. *Combined features*

Fig. 5 demonstrates the classification results for the test data using both features in terms of Acc, PPV, NPV, and AUC for all three classifiers. As a result of the comparison, AdaBoost is clearly superior to the other classifiers. When fed the 30% of the unseen data to the classifiers, the AdaBoost outperformed the other classifiers by showing the mean Acc, PPV, NPV, and AUC of 80.24%, 78.94%, 80.64%, and 0.86, respectively. Followed by that, the SVM showed the Acc, PPV, NPV, and AUC of 76.54%, 76.66%, 76.51%, and 0.82 respectively. When kNN was applied, the results were 75.30%, 68.42%, 77.41%, and 0.68 for the Acc, PPV, NPV, and AUC, respectively.

According to the T-test, there is significant difference in the obtained results between Adaboost and the other classifiers in terms of Acc, PPV, and NPV (p<0.05).

V. Discussion

The objective of this research was to present an efficient and reliable feature set that would need no initial calibration for the detection of cognitive load using the analysis of low-channel prefrontal EEG data. Since most of the current methods rely on multi-channel EEG recordings, they can hardly be used in real-life applications due to the inconvenience of wearing an EEG cap with several electrodes and attachments. Furthermore, multi-channel EEG configuration requires covering hair-bearing areas of the scalp which are associated with more noise [4]. By employing two prefrontal EEG channels, the user is provided with greater comfort since all electrodes are placed on the forehead.

We aimed to develop a low-complexity algorithm that can be applied to EEG measured using commercial headbands. To this end, we used nonlinear calibration-free measures, i.e., WLE and SE, which have been proven to be powerful for the discrimination of mental states [18] [19].

Some studies addressed cognitive load classification based on the employment of several biomedical signals such as ECG, Heart Rate, Galvanic Skin Response, and Respiratory Rate [11]. Unarguably, the main source of mental states is the brain while the other biomedical signals indicate the response of the autonomous nervous system to cognitive load. Thus, detecting the mental states of the main source is of great importance for real-life applications. In addition, employing several biomedical signals may require more instruments which increases the wearable complexity. The proposed algorithm achieved lower accuracy compared [9] but, that research enjoyed a variety of biological signals and variables which increase the complexity of the method. Unlike [9] our method possesses lower complexity which brings it more appropriate to use in real-life applications by far. While [10] confined low beta analysis and reached an accuracy of 71.4%, we considered all EEG bands and their information to obtain much higher accuracy as the result reveals other EEG bands carry on valuable information in cognitive workload occasions. Although based on the purpose of the research utilizing initial free features to employ in commercial headbands, the promising results obtained in

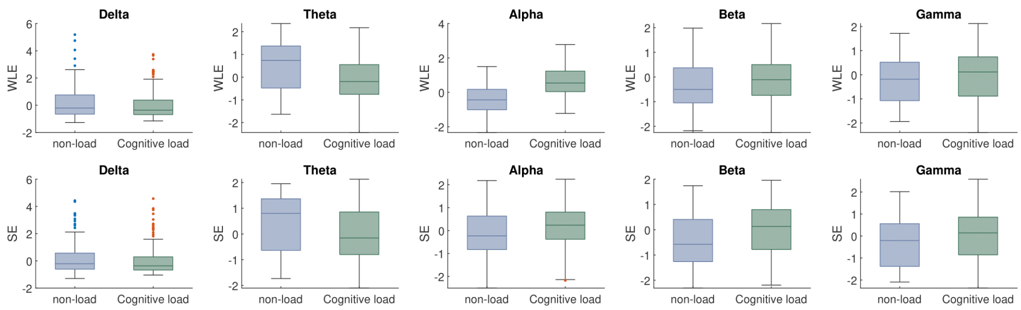

Fig. 4. Boxplots of the WLE and SE features in each sub-band.

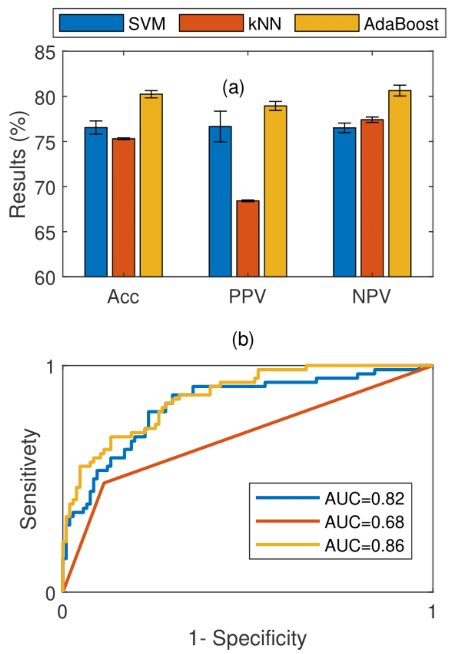

Fig. 5. a) Comparison of three classifiers' results using both features in terms of Acc, PPV, and NPV. The AdaBoost is superior to the other classifiers. b) The ROC curves and corresponding AUC values obtained by the SVM, AdaBoost, and kNN using both features

this paper, a couple of issues exist to be considered for future works. Firstly, while we have only examined two levels of cognitive load, we should extend the study in the future to consider three classes, i.e., no cognitive load, middle load, and high cognitive load [8]. Secondly, the inter-subject variability, due to the small number of subjects in the database, was not investigated. As a result, a larger number of subjects will be needed to investigate the performance of the proposed method. Thirdly, the performance of the proposed method should be further investigated on different commercial EEG headbands with different channel configurations. The last issue is to consider other classifiers that are not commonly used in EEG-based cognitive load detection. Fourthly, advanced classifiers, e.g., random forest, can improve classification results.

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