Fusion of EEG and Eye Blink Analysis for Detection of Driver Fatigue

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***Abstract*— *Objective*: The driver fatigue detection using multi-channel electroencephalography (EEG) has been extensively addressed in the literature. However, the employment of a single prefrontal EEG channel should be prioritized as it provides users with more comfort. Furthermore, eye blinks from such channel can be analyzed as the complementary information. Here, we present a new driver fatigue detection method based on simultaneous EEG and eye blinks analysis using an Fp1 EEG channel. *Methods*: First, the moving standard deviation algorithm identifies eye blink intervals (EBIs) to extract blink-related features. Second, the discrete wavelet transform filters the EBIs from the EEG signal. Third, the filtered EEG signal is decomposed into sub-bands, and various linear and nonlinear features are extracted. Finally, the prominent features are selected by the neighbourhood components analysis and fed to a classifier to discriminate between fatigue and alert driving. In this paper, two different databases are investigated. The first one is used for parameters' tuning of proposed method for the eye blink detection and filtering, nonlinear EEG measures, and feature selection. The second one is solely used for testing the robustness of the tuned parameters. *Main results*: The comparison between the obtained results from both databases by the AdaBoost classifier in terms of sensitivity (90.2% vs. 87.4%), specificity (87.7% vs. 85.5%), and accuracy (88.4% vs. 86.8%) indicates the reliability of the proposed method for the driver fatigue detection. *Significance*: Considering the existence of commercial single prefrontal channel EEG headbands, the proposed method can be used to detect the driver fatigue in real-world scenarios.**

***Index Terms*—* EEG, eye blink, fatigue, alert, driver.**

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I. Introduction

GLOBALLY, it is estimated that 14-20% of road accidents occur due to the driver fatigue [1]. Just in the Unites States, a study by the AAA foundation for traffic safety approximated that annually more than 328,000 crashes are caused due to the driver fatigue, of which 109,000 results in an injury and about 6,400 are fatal [2]. Thus, the detection of fatigue and alarming the driver is of great importance for reducing road accidents and saving lives [3].

In general, two main modalities have been widely investigated for the detection of driver fatigue in literature; subjective and physiological approaches [4]. The subjective strategies such as self-reported fatigue [5] and video measurement of facial expressions [6] or head postures [7] are prone to the biased individualistic feedback and privacy violation [8], respectively. The latter is the analysis of physiological signals such as electrocardiography (ECG) [9], photoplethysmography (PPG) [10], electrooculography (EOG) [11], and electroencephalography (EEG) [12], whose reliability and effectiveness have been widely demonstrated through various algorithms and subsequent conclusions. Amongst the physiological signals, EEG is recognized as the most effective one as the electrical activity of brain contains inherent information associated with the underlying processes of fatigue [13]. Consequently, the discrimination between the fatigue and alert driving using EEG has been widely addressed in literature [14], [15].

Although several EEG-based studies reported the accuracy above 90% for the detection of driver fatigue, a majority of them have considered multi-channel EEG recordings, e.g., [8], [12], [16], [17], [18], which increases the complexity of wearable instrumentation [19] and is cumbersome for the long-term driving. Yet, the advent of low-cost portable single channel EEG headbands has provided a new possibility for the driver fatigue detection in the real-world scenario [20], [21]. On the other hand, recording EEG from the prefrontal cortex can be more convenient since it is a non-hair bearing area, i.e., less suspicious to noise [22], and can provide the user with more comfort by allowing them to use the headrest during driving [23]. Moreover, the emergence of eye blinks in prefrontal EEG signals can be also used to characterize the fatigue driving [24]. Hence, algorithms capable of detecting the driver fatigue by using a single prefrontal EEG channel should be prioritized.

According to the best of authors knowledge, only a few studies have investigated the effectiveness of prefrontal EEG signals for the detection of driver fatigue. Ogino and Mitsukura [25] employed the power spectral density of an Fp1 EEG channel and reported the accuracy of 64.9% by a support vector machine (SVM) classifier. Qiu et al. [26] investigated the performance of three entropy features, i.e., permutation, sample, and fuzzy, for detection of the driver fatigue using Fp1 and Fp2 EEG channels and reported the accuracy of 95%. In another study, Cai et al. [27] derived 9 entropy measures from Fp1 and Fp2 channels and reported the accuracy of 94% by the light gradient boosting machine classifier. More interestingly, Ko et al. [23] showed that extracting blink-related features from a prefrontal EEG channel enhanced the accuracy of driver fatigue detection when employed alongside the EEG. Indeed, despite the aforementioned studies that considered eye blinks as a source of artifact in prefrontal EEG channels that should be removed before the EEG analysis, it was shown that extracted blink features combined with the band power analysis of EEG would improve the monitoring of driver's cognitive state. Followed by [23] and [24], in our previous study [28], we showed that the eye blinks have both beneficial and detrimental influence on the prefrontal EEG data for the driver fatigue detection. After extracting the blink-related measures and removing eye blinks from the Fp1 and Fp2 channels, the relative band power of the filtered EEG signals and blink features were fed to a SVM and the mean accuracy of 78.2% was achieved.

In spite of the promising results reported by the mentioned studies, employing only one database for the detection of driver fatigue is a potential limitation. In particular, when using nonlinear measures such as entropy, the interchangeability of tuned features for other databases is of great importance. In this paper, we present a new method for the detection of driver fatigue using a single Fp1 EEG channel, where its performance is evaluated by two different databases; the first one is used for adjustment of the proposed method's parameters, whereas the second one is used to evaluate the effectiveness of tuned parameters.

Generally, the onset of fatigue in EEG might be better revealed by its sub-bands analysis [3], [22], [23], [25]. On the other hand, as shown in the context of consciousness states classification studies that EEG may show more complexity when the subject is in an alert state [29], [30], [31], it can be expected that complexity measures will be good indicators for the detection of driver fatigue. Furthermore, it has been shown that blinks have both beneficial and detrimental influence on EEG for the detection of driver fatigue [28]. Supported by the mentioned presumptions, our proposed method firstly identifies eye blink intervals (EBIs) in EEG to extract blink-related features. Secondly, EBIs are filtered from the EEG by the discrete wavelet transform (DWT). Thirdly, the filtered EEG is split into its sub-bands for the extraction of relative band power and nonlinear measures. Finally, the prominent features are selected by the neighborhood component analysis (NCA) algorithm and fed to different classifiers for discrimination of the fatigue and alert driving.

II. Materials and Methods

A. Data

In this paper, we used two different databases to validate the performance of proposed method. The first one was used for tuning the parameters of proposed method, whereas the second one was only employed for assessing the reliability of tuned parameters. To increase the analogy of data analysis with a consumer prefrontal EEG headset (NeuroSky) [32], only the Fp1 channel was used.

1) Database A: This database consists of EEG data recorded from 12 healthy male participants aged between 19-24 in a highway driving simulation experiment [33]. The experiment consisted of two phases. In the first phase, the subjects started the experiment for 20 minutes and then the last 5 minutes were labeled as the alert state. In the second one, the subjects kept performing the experiment for 40±100 minuets until the results of self-report fatigue survey indicated that the subject was in a fatigue state, and the last 5 minutes were labeled as the fatigue state. In total, 30 EEG channels were recorded with the sampling rate of 1000 Hz. The Fp1 EEG channel was referenced to the linked mastoid at A1. In addition, this database contains vertical EOG signals recorded simultaneously with the EEG. In order to produce more fatigue and alert states trials, the EEG data of each subject were segmented into 20s long epochs [23], where a total of 180 fatigue and 180 normal trials were formed.

2) Database B: This database comprises of EEG data collected from 16 subject (8 male) aged from 17 to 25 in a platform environment with a static simulator [26]. To collect the EEG data, a 32 channels EEG cap system, referenced to the A2 mastoid with sampling rate of 1000 Hz was used. Additionally, vertical EOG signals were recorded concurrently. All subjects were healthy during the experiment week, and had a proper sleep in night before the experiment. They were also prohibited to consume beverages that contain caffeine or alcohol. Before performing the experiment, the subjects were familiarized with the experimental environment and operation process. After ensuring subjects' preparation and calmness during the experiment, laboratory assistants commenced to record 5 minutes EEG data, which were labeled as the alert state. After that, subjects were asked to keep driving till the Li's subjective fatigue scale and Borg's CR-10 scale indicated that the subject was in the fatigue state. Then, the last 5 minutes of EEG data were labeled as the fatigue state. Accordingly, 480 20s long EEG epochs in fatigue and alert states are formed, of which 240 belong to the fatigue state.

B. Theoretical Framework

1) Moving Standard Deviation: The basis of moving standard deviation (MSD) is to perform window sliding on the whole sequence of a signal to compute the standard deviation values of the local k data points, where k is the width of the window. The two-sided MSD of the signal $x[n]$ with the length of N is given by

$$s[n] = \frac{1}{W}\sqrt{\left[\sum_{i=-k}^{k} x^2[n+i] - \frac{1}{W}\left(\sum_{i=-k}^{k} x[n+i]\right)^2\right]}, \quad (1)$$

where $W = 2k + 1$ is the sliding window length and $n = k+1, k+2, \ldots N-k$ [34]. Due to the substantial differences in the inherent characteristics of eye blink and EEG signal, it is expected that EBIs be reflected in the amplitude of the MSD sequence obtained from the contaminated EEG signal.

2) Discrete Wavelet Transform: The basis of the DWT is to break down the given signal $x[n]$ into high (detail, $d[n]$) and low (approximation, $a[n]$) frequency components by passing it through series of low- and high-pass filters. Based on multiresolution analysis, the given signal is firstly decomposed into one approximation ($a_1[n]$) and one detail ($d_1[n]$) components. Then, the decomposition process is continued by splitting $a_1[n]$ into further approximation and detail components. This procedure is repeated l times (decomposition level). $x[n]$ can be reassembled as follows:

$$x[n] = \sum_{i=1}^{l} d_i[n] + a_l[n], \quad (2)$$

The frequency band of each approximation and detail components is calculated by

$$a_i = \left[0, \frac{Fs}{2^{i+1}}\right], \quad d_i = \left[\frac{Fs}{2^{i+1}}, \frac{Fs}{2^i}\right], \quad (3)$$

where Fs is the sampling frequency of the given signal [35]. Regardless of the decomposition level, selection of the mother wavelet plays an important role for analyzing the given signal. Such selection is generally performed based on the resemblance of the mother wavelet and the signal under analysis. In this paper, $db4$ has been used as the mother wavelet since it was shown suitable for the EEG analysis to detect the driver fatigue [23], [36].

C. The Proposed Method

The block diagram of proposed method is illustrated in Fig. 1. As shown, firstly, the raw EEG signal is band-pass filtered for the noise reduction and re-sampled for reducing the computational burden. Secondly, EBIs are identified using the MSD algorithm and three blink-related measures are dervied. Thirdly, the identified EBIs are filtered from the EEG signal based on the DWT algorithm, and then linear and nonlinear features are extracted from the filtered EEG sub-bands. Finally, a subset of prominent features are selected and fed to different classifiers to discriminate between the fatigue from alert driving states. The detailed explanation of proposed method is described in subsections below.

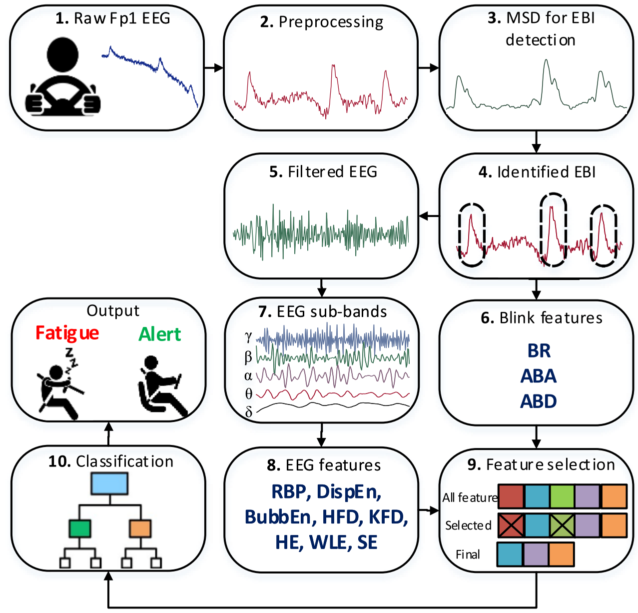

Fig. 1. Block diagram of the proposed method for classifying the fatigue and alert driving using a single Fp1 EEG channel.

1) Pre-Processing: In order to remove high and low frequency artifacts from the EEG data, a zero-phase fourth order Butterworth band-pass filter with the cut-off frequencies at 1 and 40 Hz is applied to the raw EEG signal. Then, the filtered signal is re-sampled to 100 Hz to reduce the computational burden.

2) Detection of Eye Blink Intervals: In order to detect EBIs, firstly, the local maxima of MSD sequence obtained from the EEG are identified. Then, those with a value greater than the modified universal threshold (Th_1) [28] are selected as the potential eye blink highest peaks (Fig. 2b)

$$Th_1 = A\left(\frac{\text{median}(|s[n]|)}{0.6745}\right)\sqrt{2\ln N}, \quad (4)$$

where $s[n]$ is the MSD of EEG, N is the signal length, and A is the scaling factor. Secondly, if the distance between two potential eye blink highest peaks is less than 0.2s, the higher peak is selected as the final candidate (Fig. 2c). Thirdly, the identified eye blink highest peaks are projected to the EEG signal. As shown in Fig. 2d, the locations of eye blink highest peaks in the EEG are not accurate. To overcome this problem, a window is formed around each identified peak with 0.2s length before and after the peak. Then, the maximum signal value within this window is considered as the highest eye blink point (Fig. 2e). After finding the highest peak of EBIs, given the fact that an EBI duration usually varies from 200 to 500ms [37], 500ms intervals (125ms pre- and 375ms post the highest amplitude peaks) are chosen as the identified EBIs (Fig. 2f). The main steps of MSD-based method for the identification of EBIs are summarized in Algorithm 1.

3) Blink-Related Features: As stated above, blink measures extracted from the EEG have been shown promising for detection of the driver fatigue. It is the common knowledge that when subjects are performing tasks requiring the visual

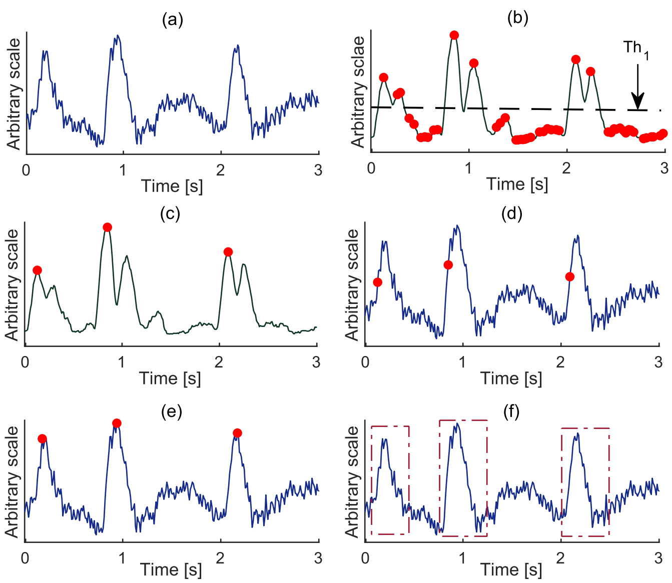

Fig. 2. An example for EBIs detection from an Fp1 EEG channel. (a): EEG signal, (b): the MSD of EEG signal with the local maxima that exceeds Th_1, (c): the MSD with the potential eye blink highest peaks, (d): the potential eye blink highest peaks of MSD projected to the EEG, (e): the corrected location of the highest eye blink peaks in EEG, and (f): the identified EBIs in EEG.

Algorithm 1 The MSD for Localization of One EBI

Input: EEG $z[n]$, Fs, k

Output: EBI highest peak n_1, EBI $z_2[n]$

Initialisation $Th1 \leftarrow 0$, $q \leftarrow [\ ]$, $r \leftarrow [\ ]$, $m \leftarrow 1$,

$s[n] \leftarrow$MSD($z[n]$, k)

$Th1 \leftarrow$ see equation (4)

for $i = 2$ to length($z[n]$) $- 1$ **do**

  if $s[i] > s[i-1]$ && $s[i] > s[i+1]$ && $s[i] > Th1$ **then**

    $q \leftarrow [q \quad i]$

  end if

end for

for $i = 1$ to length(q) $- 1$ **do**

  $d \leftarrow$ abs($q_i - q_{i+1}$)

  $r \leftarrow q_i$

  while $d < 0.2 \times Fs$ **do**

    $r \leftarrow find(s \leftarrow max(s(q_i), s(q_{i+1}))$

    $m \leftarrow m + 1$

  end while

  $i \leftarrow i + m$

  $onset_1 \leftarrow r - 0.2 \times Fs$

  $offset_1 \leftarrow r + 0.2 \times Fs$

  $z_1[n] \leftarrow z[onset_1 : offset_1]$

  $n_1 \leftarrow$ find($z_1[n] \leftarrow$ Max($z_1[n]$))

  $onset_2 \leftarrow n_1 - 0.125 \times Fs$

  $offset_2 \leftarrow n_1 + 0.375 \times Fs$

  $z_2[n] \leftarrow z[onset_2 : offset_2]$

end for

return n_1, $z_2[n]$

attention, e.g., driving, they blink less to stay more focused [38], [39]. Consequently, given the fact that the concentration

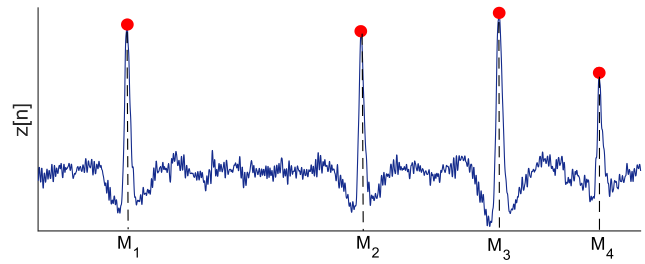

Fig. 3. An example for extraction of the blink-related features from an Fp1 EEG channel. M stands for the locations of four (i=4) blinks.

level decreases in the fatigue state, blink-related measures can be of discriminative power in the classification between alertness and fatigue states. In particular, it was demonstrated that while the eye blink rate increases in the fatigue state, its amplitude decreases [23]. Justified similarly, three blink measures called blink rate (BR), average blink amplitude (ABA), and the average distance between the blinks (ABD) are computed. Let the $z[n]$, $n = 1, 2, \ldots N$ be the 20s contaminated EEG signal, $M = M_1, M_2, \ldots M_i$ which $M \in n$ be the location of detected eye blinks, and i be the number of detected blinks (Fig. 3). The BR, ABA, and ABD are expressed as follows:

$$\mathrm{BR} = \frac{i}{20}, \tag{5}$$

$$\mathrm{ABA} = \frac{\sum(z[M_i])}{i}, \tag{6}$$

$$\mathrm{ABD} = \frac{\sum(M_i - M_{i-1})}{i-1}, \tag{7}$$

4) Filtering of Eye Blink Intervals From EEG: Although blink-related features extracted from EEG are promising for the detection of fatigue driving [23], [24], eye blinks have been shown to have an adverse influence on the analysis of EEG due to their amplitude [28]. To minimize such a negative influence, given the sampling rate and the frequency range of eye blinks in EEG, i.e., 0.5 to 7.5 Hz, the identified EBIs are filtered by hard-thresholding DWT with three decomposition level, where those values of component at each level that transcend the universal threshold are settled to zero. Then, the filtered EEG signal is restored by inverse DWT of the thresholded components.

5) EEG Sub-Bands Extraction: One of the main applications of DWT in EEG studies is to extract its sub-bands [35], [36]. Given the reduced sampling rate of EEG and equation (3), four levels DWT can extract EEG sub-bands, where detail components of the first, second, third and forth level associate with gamma (γ, >25 Hz), beta (β, 12.5-25 Hz), alpha (α, 6.25-12.5 Hz), and theta (θ, 3.125-6.25 Hz), respectively, and the forth level of approximation component corresponds to the delta (δ, <3.25 Hz) band.

6) EEG Features: After eye blink removal and splitting the EEG into its sub-bands, eight features namely the relative band power (RBP), wavelet log-energy entropy (WLE), Shannon entropy (SE), dispersion entropy (DispEn), bubble entropy (BubbEn), Higuchi's fractal dimension (HFD), Katz's fractal dimension (KFD), and Hurst exponent (HE) are extracted from each sub-band. Following the presumption that altering the power ratio of EEG sub-bands is correlated with the fatigue state [3], [23], [25], i.e., the power ratio of EEG higher frequency bands decrease while does the opposite for the lower bands, it can also be expected that the extraction of nonlinear measures from EEG sub-bands is more effective than the signal itself. Therefore, in addition to the RBP, different fractal dimension (FD) and entropy measures are also extracted. The FD features measure the degree of signal's complexity and self-similarity by evaluating how quickly the signal increases or decreases with altering the scale. On the other hand, entropy features assess the signal's uncertainty. As EEG is assumed to show more complexity and uncertainty in the alert state [29], [30], such measures can be good markers for the fatigue detection. The optimization of the nonlinear features are described in section III-B.

7) Feature Selection: Totally, 43 features (3 blink-related) are extracted from the EEG signal. To reduce the dimension of feature vector, we employ the NCA [40], which selects the best feature subset by maximizing an object function, assessing the mean leave-one-out classification accuracy over the training data. Indeed, NCA outputs a weighting vector related to the feature vector by optimizing the nearest neighbour learning classifier. The reason for using the NCA over the other feature selection methods is that it is a non-parametric algorithm, therefore, no specific regulations are required.

8) Classification: After selecting the prominent features, they are normalized using z-score strategy and randomly divided into the training-validation (70%) and test (30%) subsets. To secure the reliability of results, the training-validation process is conducted according to the 10-fold cross-validation (CV) and the testing is only established on the unseen subset. In this paper, we used SVM, linear discriminant analysis (LDA), k-nearest neighbor (kNN), and AdaBoost, artificial neural network (ANN), and random forest (RF) models to classify between the fatigue and alert driving states. The motivation behind using these models is their proven feasibility for the EEG-based studies, in particular, driver fatigue detection [18], [19], [22], [41]. The optimization of the model's hyperparameters are conducted during the training-validation step by Bayesian optimization method [42].

D. Evaluation Criteria

1) Eye Blink Detection and Filtering: To investigate the performance of eye blink detection, the critical success index (CSI) is used as follows:

$$\mathrm{CSI} = \frac{T_p}{T_P + F_N + F_P}, \tag{8}$$

where T_P, F_N, and F_P represent the number of correctly, missed, and falsely detected eye blinks. Regarding the eye blink filtering, given that both databases contain the concurrent recorded EOG signals, the signal to noise ratio (SNR) is utilized as follows:

$$\mathrm{SNR} = 10 \times log_{10}\left(\frac{\frac{1}{N}\sum_{i=1}^{N} PSD_{EEG}}{\frac{1}{N}\sum_{i=1}^{N} PSD_{EOG}}\right), \tag{9}$$

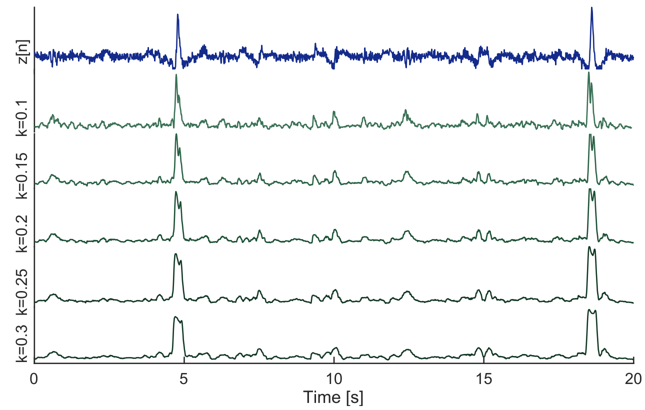

Fig. 4. The contaminated EEG (dark below) and its corresponding MSDs with different window size (green).

where PSD stands for the power spectral density [43]. It should be noted that SNR of raw EEG is computed before applying any filtering and SNR of filtered EEG signal is computed based on filtered EEG and estimated EOG signal by the proposed method.

2) Model Assessment: The performance of models is assessed according to the sensitivity (Sen), specificity (Spe), accuracy (Acc), and area under the curve (AUC) as follows:

$$\mathrm{Sen} = \frac{T_P}{T_P + F_N} \times 100, \tag{10}$$

$$\mathrm{Spe} = \frac{T_N}{T_N + F_P} \times 100, \tag{11}$$

$$\mathrm{Acc} = \frac{T_P + T_N}{T_P + T_N + F_N + F_P} \times 100, \tag{12}$$

$$\mathrm{AUC} = \int \mathrm{Sen}(T)(1\text{-}\mathrm{Spe})'(T)dT, \tag{13}$$

where T_P and F_N stand for the number of correctly and wrongly classified fatigue cases, T_N and F_P represent the number of correctly and wrongly classified normal cases, and T is the binary threshold of the classifier.

III. Results

In this section, the experimental results obtained from both databases are described. It should be noted that the regulation of required parameters for eye blink detection and nonlinear measures, as well as the feature selection, have been conducted on the EEG data from the Database A. Then, the tuned parameters and selected features were used for the analysis of the Database B.

A. Eye Blink Detection, Filtering, and Feature Extraction

The MSD algorithm requires two parameters to be tuned for EBIs detection; the window length k and the scaling coefficient of universal threshold A. Regarding the window length, we have considered values from 0.1s to 0.3s with a step size of 0.05s. Although no noticeable difference was found in the morphology of EBIs, we selected $k = 0.2s$ (Fig. 4).

Regarding the scaling factor of universal threshold, values from 0.25 to 1 with the a step size of 0.25 were investigated.

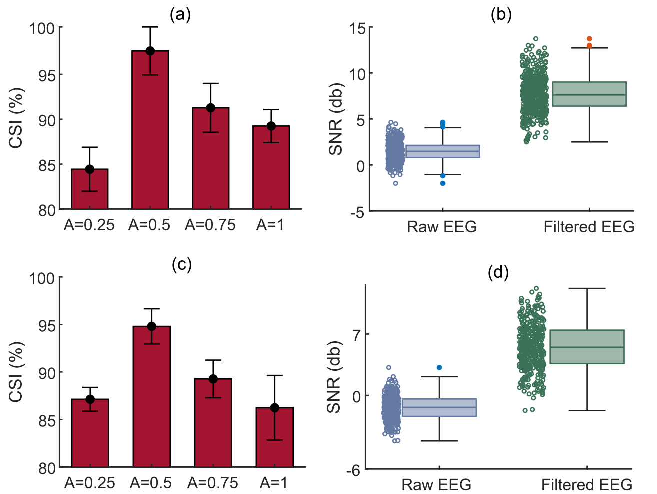

Fig. 5. Results for EBIs detection and filtering. (a)-(b): Database A, and (c)-(d): Database B.

TABLE I
THE COMPARISON BETWEEN EYE BLINK DETECTION METHODS IN TERMS OF MEAN ± SD OF CSI VALUES

Database	MSD	VME
Database A	96.8 ± 3.2	94.4 ± 4.3
Database B	94.6 ± 3.7	92.2 ± 5.3

The best fit, $A = 0.5$, was selected based on the highest mean of CSI (Fig. 5a). Afterwards, the identified EBIs were filtered based on the DWT. Given having the simultaneous recorded the vertical EOG, the SNR values were compared before and after the filtering (Fig. 5b). The adequacy of the tuned parameters for the detection and filtering of EBIs for Database B was also confirmed in Fig. 5(c-d).

In order to compare the performance of eye blink detection of the proposed method with our previous study [28], the CSI in terms of mean ± standard deviation (SD) is displayed in Table I.

Although the MSD outperformed the VME, no statistical difference was observed between the obtained results ($p>0.05$). Yet, the MSD performed faster than the VME as less computations are required.

Fig. 6 compares the blink-related features between alert and fatigue states extracted by the proposed method from the Database A. It should be noted that outliers have been removed from the illustration for clearer visual comparison.

B. Tuning EEG Nonlinear Features

In order to tune the parameters of the employed nonlinear measures that required optimization, i.e., DispEn, BubbEn, HFD, and KFD, we considered the lowest p value of conducted Wilcoxon Rank-Sum Test between the alert and fatigue driving cases [35]. Regarding the KDF and HFD, the maximum interval time, K_{max}, that FD values are computed in, values from 2 to 10 were varied, and $K_{max}=4$ was found as the optimal value. Regarding the embedding dimension of BubbEn, values from 4 to 16 were tested. We selected

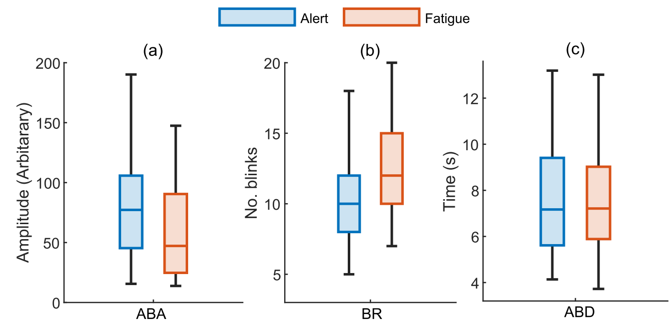

Fig. 6. Boxplots of extracted blink features from Database A. (a): ABA, (b): BR, and (c): ABD.

TABLE II
CLASSIFICATION RESULTS BASED ON DIFFERENT THE FEATURE TYPE USING ALL MODELS

Feature type	RBP EEG			Nonlinear EEG		
Classifier	Acc	Sen	Spe	Acc	Sen	Spe
SVM	61	59	63	71	70	73
LDA	63	67	58	69	69	70
kNN	59	58	59	68	69	68
AdaBoost	67	66	69	78	80	79
ANN	61	70	52	66	64	69
RF	63	58	66	72	70	73

Feature type	All EEG			Blink		
Classifier	Acc	Sen	Spe	Acc	Sen	Spe
SVM	76	78	74	52	58	48
LDA	71	69	73	56	54	57
kNN	74	71	76	60	67	62
AdaBoost	81	80	81	70	69	71
ANN	71	73	69	61	60	61
RF	78	75	80	67	70	65

the embedding dimension of 8 as a good fit. Regarding the DispEn, we tested several configurations, and found the embedding dimension of 4, 2 number of classes, and the time lag of 1 as a good fit.

C. Classification Results

1) Classification Based on the Feature Type: Table II displays the classification results obtained by each model using a single feature type, i.e., linear EEG features (RBP), nonlinear EEG features, combination of RBP and nonlinear EEG features, and blink-related features, from Database A. It is worth to mention that the analysis has been performed based on the 10-fold CV. As displayed, the best feature type is the combination of linear and nonlinear EEG features. Nonetheless, it is possible to enhance the classification results by selecting the most relevant feature from all categories. Indeed, feature selection can help to remove redundant and irrelevant features, and consequently, enhance the prediction power of the models.

2) Classification Based on the Selected Feature: Table III displays the weighted features using NCA, optimized by stochastic gradient descent algorithm. The features with a weight value greater than 0.5 (18 features) are selected for the classification.

Table IV presents the training and validation results of both databases obtained by all four classifiers. As can be seen,

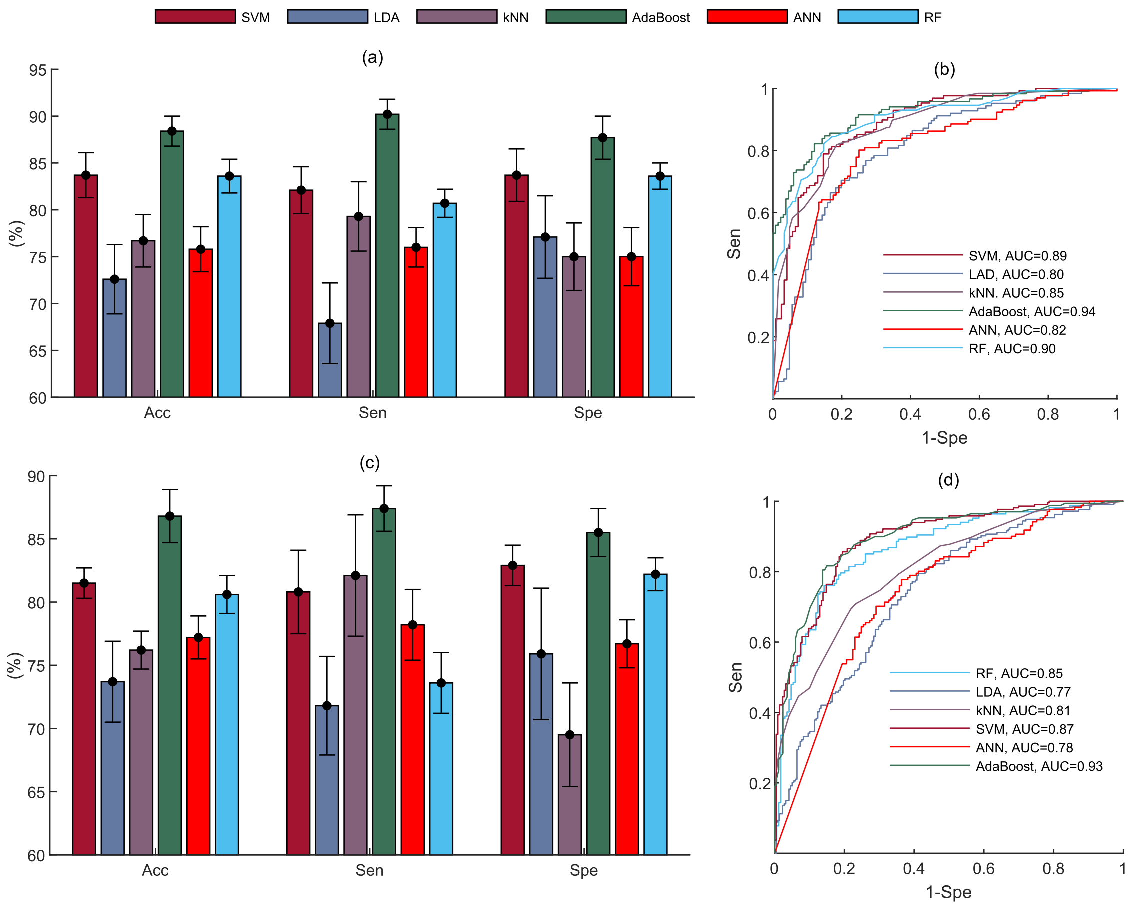

Fig. 7. Classification results for the detection of driver fatigue by all models. (a)-(b): Database A, and (c)-(d): Database B.

TABLE III
THE WEIGHTED FEATURES BY USING NCA, (SELECTED FEATURES ARE IN BOLD)

Features	Weights				
	EEG bands				
	Delta	Theta	Alpha	Beta	Gamma
RBP	**0.59**	0.13	0.21	**1.84**	0.31
DispEn	**0.74**	0.12	0.05	0.31	**0.56**
BubbEn	0.07	0.08	0.14	0.01	**0.74**
HFD	0.11	0.34	**0.86**	**1.42**	**0.85**
KFD	0.09	**1.26**	**1.71**	0.33	**1.16**
HE	0.02	0.36	0.01	0.01	**1.14**
WLE	**1.38**	**1.73**	0.35	0.13	**1.98**
SE	0.08	**0.88**	0.04	0.24	0.37
blink					
BR	**1.12**				
ABA	**0.79**				
ABD	0.05				

TABLE IV
THE AVERAGE TRAINING-VALIDATION RESULTS OF ALL CLASSIFIERS FOR BOTH DATABASES (A AND B INDICATE THE DATABASES)

		Training			Validation		
	classifier	Acc	Sen	Spe	Acc	Sen	Spe
A	SVM	99.6	99.5	99.7	87.6	86.5	89.2
	LDA	96.1	95.4	96.7	81.2	82.3	80.5
	kNN	98.4	97.2	99.3	83.6	84.2	82.7
	AdaBoost	99.8	100	99.2	89.2	88.4	90.8
	ANN	98.4	97.1	99.5	80.9	81.4	80.5
	RF	99.1	99.2	98.6	88.6	87.6	88.1
B	SVM	98.5	98.1	98.9	84.3	84.8	83.6
	LDA	95.7	92.7	97.8	81.8	82.6	81.1
	kNN	97.4	98.2	96.9	83.7	85.2	81.3
	AdaBoost	99.5	99.9	99.3	89.6	90.4	88.9
	ANN	97.8	96.9	98.3	79.8	85.4	71.9
	RF	99.7	100	99.9	86.4	87.8	85.6

the AdaBoost outperformed the others models in terms of validation. It is also worth to be mentioned that the SVM with radial basis function (RBF) kernel and the AdaBoost with gentle ensemble aggregation method were used for both databases. Regarding the kNN, 5 and 4 number of neighbors with the Euclidean distance for Database A and B were employed, respectively.

Fig. 7 demonstrates the classification results of the unseen testing data in terms of Acc, Sen, Spe, and AUC for all four models. The comparison confirms the superiority of AdaBoost over the other models. When fed the selected feature set of Database A to the models, AdaBoost classifier outperformed the others by showing the mean Acc, Sen, Spe, and AUC of 88.4%, 90.2%, 87.7%, and 0.94, respectively. Followed by that, SVM with the mean Acc of 83.7% was the second best model (Fig. 6a-b). Based on the performed independent two-sample t-test, there is a statistically significant difference between the Acc, Sen, and Spc values of AdaBoost and other classifiers (p<0.05). Regarding the Database B, (Fig. 6c-d), similar to the Database A, the AdaBoost model achieved the highest mean Acc, Sen, Spe, and AUC values of f87.4%, 85.5%, 86.8, and 0.93, respectively. Except for the Spe values of AdaBoost, SVM, and RF, there is a statistically significant difference between the obtained results by AdaBoost and other classifiers ($p<0.05$).

D. Comparison With State-of-the-Art Methods

Table V displays the comparison between the proposed and state-of-the-art methods in terms of the number of channels, subjects, and databases, as well as the epoch length, training-testing strategy, and average classification metrics. It is worth to be mentioned that we have only considered studies that used EEG data from the prefrontal cortex.

Although, due to using different databases, epoch length, subjects, and training-testing strategy, it is inequitable to quantitatively compare performance of the proposed method with other studies, the consistency of obtained results from two different databases using the proposed method can not be neglected. Indeed, the reliability of our method was proven based on two different databases, which is not the case for the mentioned studies. In addition, studies [26] and [27] employed two prefrontal EEG channels for the driver fatigue detection. According to the best of our knowledge, currently, no such EEG headbands with this channel configuration exist in the market. Nevertheless, it should be mentioned that the reported results from [23] are based on leave-one-subject-out (inter-subject) cross-validation, i.e., verifying the possibility of generalized model establishment, which was not investigate here.

IV. Discussion

The objective of this research was to present a new method for the detection of driver fatigue based on concurrent analysis of EEG and blinks through a single prefrontal channel, oriented towards the pragmatic limitations of the current studies. The most of the current methods were developed based on multi-channel EEG recordings, not suitable for a practical application as wearing an EEG cap with several accessories (electrodes and cables) may inconvenience the user for the long-term driving. Furthermore, multi-channel EEG configuration usually covers hair-bearing areas of the scalp that are more susceptible to noise [22], [23]. Contrastingly, employing a single prefrontal EEG channel provides the user with more comfort as only one electrode is placed on the forehead, which is a hairless area. Moreover, the prefrontal EEG signal contains eye blinks changes that have been shown to correlate with the transition from the alert to the fatigued state [23], [24], [38], therefore, blink-related measures can be extracted from the prefrontal EEG channel and used as a complementary information.

On the other hand, a few studies that addressed the fatigue driving detection based on the single or low prefrontal EEG channels only employed one database to develop and test the performance of the proposed methods [23], [25], [26], [27], [28]. Unarguably, the interchangeability of methods presented for detecting the driver fatigue using different databases, which is of great importance for the real-world applications, was undermined in literature. To overcome the mentioned problem, we assessed the effectiveness of proposed method in detecting the fatigue driving by employing two databases; the first database was used for parameters' tuning and the other for the testing.

A. Eye Blink Intervals Detection and Filtering

Due to both beneficial and detrimental influence of eye blinks on EEG-based fatigue driving detection [28], a hybrid method based on MSD and DWT was used to locate the EBIs, extract blink related features, and then filter them out from the EEG signal. As displayed in Fig. 5, while using different databases, the proposed MSD-DWT showed the comparable performance for eye blink detection and filtering, indicating its reliability for an unseen database. The main advantage of MSD-DWT is its simplicity, making it a suitable candidate for the real-time applications. Indeed, the computational complexity of the MSD-DWT is lower than the method proposed in [28] ($\mathcal{O}(\mathcal{N})$ vs. $\mathcal{O}(\mathcal{M}\mathcal{N}\log\mathcal{N})$), where $\mathcal{M}$ stands for the iteration of eye blink mode extraction.

B. Interchangeability of Proposed Method

Considering the fact that the interchangeability of a proposed feature set for other EEG signals recorded with distinctive characteristics plays a vital role for real-world applications, we employed two different databases; one was used for such tuning, whereas the other one was used only for testing. When comparing the obtained results by the AdaBoost classifier from Database A and B, the Database A only gained 2.8%, 2.2%, and 1.6% higher mean for the Sen, Spe, and Acc, respectively, indicating the interchangeability of the tuned parameters of used nonlinear measures. Analogously, the obtained average accuracy results by other models from both databases also showed less than 2% difference. Nevertheless, it should be noted that one cannot deduct that the power of interchangeability of the proposed method is greater than methods under comparison as such test has not been done.

Even though [26] and [27] outperformed the proposed method in terms of classification metrics, these studies have some limitations. The former only reported results on the male subjects. This is while the some studies showed the difference of EEG characteristics between male and female [44]. The latter also used some entropy measures, e.g., fuzzy, which require tuning of several parameters. As it was already mentioned, it is important to evaluates the reliability of tuned feature with other databases.

C. Directions for Future Work

Although the reported results are promising, there are a few issues that must be considered for the future work. Firstly, due to small number of subjects in each database, the inter-subject variability analysis has not been addressed here. Therefore, the performance of proposed method should be further investigated with a larger number of subjects. Secondly, we have only investigated 20s long EEG epochs for the detection of driver fatigue. Although it has been

TABLE V
THE COMPARISON BETWEEN THE PROPOSED AND STATE-OF-THE-ART METHODS. LOSOCV AND LOOCV STAND FOR LEAVE-ONE-SUBJECT-OUT AND LEAVE-ONE-OUT CROSS-VALIDATION, RESPECTIVELY

study	Channel	No. Database	Epoch length	No. Subjects	Training-testing strategy	Mean Acc	Mean Sen	Mean Spe
[23]	Fp1	1	20s	15	LOSOCV	68.0	58.0	73.0
[25]	Fp1	1	10s	29	10-fold CV	72.7	88.7	45.2
[26]	Fp1 &Fp2	1	1s	16	10-fold CV	95.3	NA	NA
[27]	Fp1 &Fp2	1	1s	35	LOOCV	94.2	94.0	94.3
[28]	Fp1 &Fp2	1	20s	12	10-fold CV	78.1	80.7	75.2
		2						
Ours	Fp1	Database A	20s	12	Random sampling	88.4	90.2	87.7
		Database A		16	Random sampling	86.6	87.4	85.5

considered as a proper length [23], [29], the analysis of a shorter time interval would be of primary importance for the real-world applications. Thirdly, we have only considered classifiers that are commonly used for the EEG-based brain computer-interface systems [8], [22]. It might be possible to improve the classification results using advanced classifiers such as XG-Boost and deep neural network. Fourthly, we have not considered EEG channel configuration based on other available EEG consumer headbands, e.g., Emotive. In the future work, we should investigate the performance of the proposed method based on other consumer EEG headbands in the market. Fifthly, we have only employed the DWT for eye blink removal from EEG. It may be possible to further improve the performance of filtering by using methods such as the wavelet packed decomposition [45]. However, it also increases the computational complexity. Lastly, we have tuned the required parameters of the proposed method based on Database A, which contains only male subjects. One may argue that it would be better to adjust parameters with the Database B as it has both genders. Yet, we decided to test performance of the proposed method on a database with both genders.

V. CONCLUSION

In this paper, we presented a new driver fatigue detection method based on simultaneous EEG and eye blinks analysis using an Fp1 EEG channel. The importance of this study was to evaluate the performance of the proposed method on two different databases, which is of great value to investigate the robustness of any method. Additionally, when regulating the parameters of the nonlinear feature of EEG, the adaptivity of the tuned features for other databases is of great importance. According to the obtained experimental results from both databases, the AdaBoost classifier outperformed the others with average accuracy of 88.4% and 86.8% for Database A and B, respectively. Considering the consistent quantitative results obtained from both databases by the AdaBoost classifier, it can be concluded that the proposed method is a reliable strategy for detecting the driver fatigue in the real-world scenario.

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