Original Research

Classifying Features of Electroencephalography Signal to Detect Driver Drowsiness in the Early Drowsy Stage

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Abstract

Background and Objective: Driver drowsiness is one of the major reasons of severe accidents worldwide. In this study, an electroencephalography (EEG) measurement-based approach has been proposed to detect driver drowsiness.
Materials and Methods: The driving tests were conducted in a driving simulator to collect brain data in the alert and drowsy states. Nineteen healthy men participated in these tests. The EEG signals were recorded from the central, parietal, and occipital regions of the brain. 12 features of EEG signal were extracted; then through neighborhood component analysis (NCA), a feature selection method, 6 features including mean, standard deviation (SD), kurtosis, energy, entropy, and power of alpha band in 11-15 Hz, where alpha spindles occur, were selected. For the drowsiness stages assessment, the Observer Rating of Drowsiness (ORD) was applied. Four classifiers including k-nearest neighbor (KNN), support vector machine (SVM), classification tree, and Naive Bayes were employed to classify data.
Results: The classification trees detected drowsiness in the early stage with 88.55%. The classification results showed that if only single-channel P4 was used for detecting drowsiness, the better performance could be achieved in comparison to using data of all channels (C3, C4, P3, P4, O1, O2) together. The best performances were 93.13% which were obtained by the classification tree based on data of single-channel P4.
Conclusion: This study suggested that the driver drowsiness was detectable based on single-channel P4 in the early stage.

Keywords: Automobile driving; Electroencephalography; Supervised machine learning; Classification

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Introduction

Driver drowsiness is a cause of fatal accidents worldwide. A drowsy driver has a low-level consciousness and cognition about the environment and drivers ability for making the right decision significantly decreases. Recent researches show that drowsy driving is as hazardous as drunk driving (1).

Researchers detect driver drowsiness based on analyzing three different categories of sensors including vehicle dynamics, facial features of drivers, and physiological signals. Physiological signals are independent of driving skills and environmental conditions, including weather conditions and vehicle and road characteristics. Therefore, they are more reliable than other above-mentioned drowsiness detection methods (2). Noori and Mikaeili detected driver drowsiness using fusion of electroencephalography (EEG), electrooculography (EOG), and driving quality signals (3). The most promising method for driver drowsiness detection in comparison with other physiological methods is the EEG signal. Researchers state that EEG signals are the most accurate and reliable indicators of sleep (2-4). Mardi et al. applied two-tailed t-test method on some chaotic features of the EEG signal including Higuchi's and Petrosian's fractal dimension and logarithm of energy of signal to detect driver drowsiness (5).

The EEG signal has specific spectral domains

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in some actions which can be classified in four important bands. Delta (0.5 to 4 Hz), theta (4-8 Hz), alpha (8-13 Hz), and beta (12-30 Hz) are four frequency bands of EEG signals. Alpha waves originate from the parietal and occipital regions of the brain in the relaxed state and closed eyes (6). On the other hand, the frontal area produces beta waves related to thinking and making a decision (7). Studies show that in the drowsiness state rather than alertness, the rate of emitting alpha waves increases (8).

The EEG signal has a non-stationary nature and considering both frequency and time domain features simultaneously is very important for performing reliable analysis. One of the most powerful methods in time-frequency analysis is the wavelet transform. Wavelet theory has been used for decades to process biomedical signals for applications including feature extraction, compression, and noise reduction (9). Wavelet analysis divides EEG data into frequency bands and can extract the overall features of non-stationary EEG (10-12). The features which are extracted from wavelet sub-bands have been highly recommended for classifying EEG data and yield precise results (9, 13-15). Subasi using discrete wavelet transform (DWT) decomposed EEG signals into the frequency sub-bands. Then the sub-band features were used as input to a classifier (13). The wavelet functions were used by Gandhi et al. to compute features such as energy, entropy, and standard deviation (SD) at the sub-bands in order to classify EEG data (9). By using different window sizes, the wavelet method can remove intrinsic noise from EEG signal and identify events in it (16). The DWT that includes high and low-pass filters is largely employed in analyzing EEG signals (17). Several studies used wavelet features for classification of EEG signals (18-20).

For driver drowsiness detection, various types of classifiers including k-nearest neighbor (KNN), support vector machine (SVM), decision tree, and Naive Bayas were used to classify the features of EEG data into two categories of "alert" and "drowsy", and their results were compared together.

This study has several significant contributions. Firstly, driver drowsiness cannot be reliably determined based on the elapsed time. As a result, the Observer Rating of Drowsiness (ORD) is replaced by the time in this study. In addition, a dominant pattern of variations in the EEG data during transition from alertness to extreme drowsiness is detected. A predominantly ascending-descending pattern was observed, ascending initially from alertness to early stage of drowsiness (ORD = 2.5) and descending again to extreme drowsiness. Furthermore, an EEG-related binormal function is elicited based on the ORD to predict drowsiness. Besides, our study shows that with five EEG features of single-channel P4, it is possible to detect drowsiness with 93% accuracy and using single channel EEG is more suitable for real-world applications.

Materials and Methods

Evaluating the drowsiness level: Driver drowsiness stage can be evaluated by expert observers. In the ORD method, three expert observers evaluated drowsiness level of subjects by assessing their driving behavior and facial signs (21). They scored drowsiness level from 1 to 5 that indicate alertness and severe drowsiness, respectively. In this paper, EEG signal was analyzed based on ORD, the drowsiness score, instead of time. It is possible for the driver to be drowsy while driving in the beginning but not to be drowsy at the end; therefore, time is not a good way to assess drowsiness patterns.

The driver exhibits little fatigue behavior at the ORD levels of 1 and 2, but at the ORD level of 2.5, at the early stage of drowsiness, some fatigue behaviors are evident.

The EEG-related features exhibit a rise during alertness to extreme drowsiness, followed by a fall. In the transition from alertness to the early stage of drowsiness state, the driver's EEG increases in magnitude and frequency as he or she tries to stay awake. It indicates that when the driver is alert, driving is an easy and habitual task for him or her, but in the moderate drowsiness state, control of vehicle and driving task becomes more complicated and harder for the driver. At this level, the driver fights against sleep but after this, the driver is starting to capitulate to falling asleep, given that in the very drowsy and extremely drowsy states, the EEG magnitude and frequency-related features decrease.

A binormal function can be used to estimate the statistical features of the stochastic EEG signal:

$$\mathrm{f(ORD)} = \mathrm{a}_1\mathrm{e}^{-(\mathrm{ORD}-\mathrm{b}_1)^2} + \mathrm{a}_2\mathrm{e}^{-(\mathrm{ORD}-\mathrm{b}_2)^2} + \mathrm{c}, \quad (1)$$

where $\mathrm{a}_1, \mathrm{b}_1, \mathrm{a}_2, \mathrm{b}_2,$ and c are function parameters.

In the ORD range of 1 to 5, figure 1 shows a typical EEG binormal function.

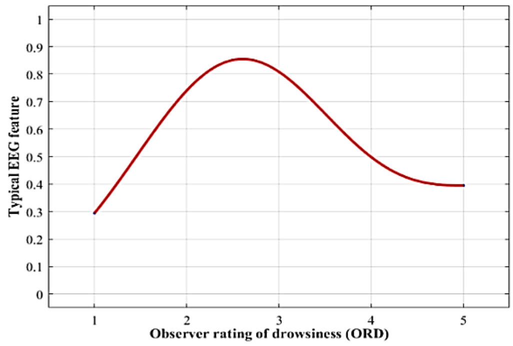


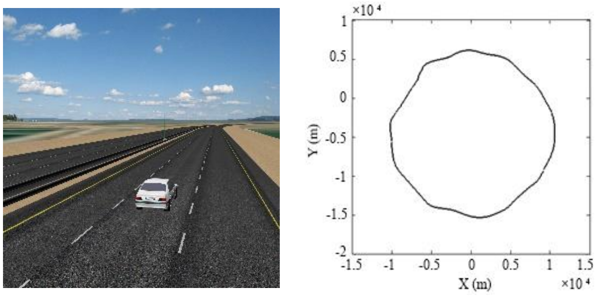
Figure 1. Binormal function of an electroencephalography (EEG) magnitude-related feature with respect to the Observer Rating of Drowsiness (ORD)

Driving simulator: The driving simulator is Nasir Semi 003 that its dynamic model has 14 degrees of freedom. The vehicle dynamic data were recorded by sample rate of 30 Hz. The driver interacts with the driving simulator by the steering wheel, shift sticks, and pedals. Figure 2 shows the driving simulator and capturing data tools.

Figure 2. Subjects driving in the driving simulator (22)

Subjects drove at the minimum and maximum allowed speeds of 80 km/h and 100 km/h on the road with 67 kilometers. Figure 3 shows the driving path. When the driver became drowsy, the vehicle would exit the road due to its quasi-circular shape. The drivers should take care to avoid sharp turns, and there were no other vehicles or pedestrians on the road.

Participants: Nineteen healthy male subjects with a valid driving license participated in the drowsiness tests.



a b

Figure 3. (a) Driving scene from a third-person point of view; (b) 67-km closed-loop driving path (22)

They aged between 26 and 50 years, with an average of 32 ± 8 years and their body mass index (BMI) was between 20 and 30 kg/m^2. All subjects had no sleep disorder and they were not addicted to cigarette, drug, and drinks. The test protocols were completely described to all participants before the tests. Data about their lifestyle, sleep, and health were collected in a self-report questionnaire. Subjects were asked to sleep at their usual sleep time in the night before the test and not drink tea or coffee during the test. Participants who did not have sufficient capability to robust against drowsiness during given time were identified by taking Maintenance of Wakefulness Test (MWT). The MWT tests were conducted a couple of days before the driving tests. During the MWT, the subjects were asked to stay alert for 40 minutes (23). Three times falling asleep in the first sleep stage or once in the other sleep stages would be considered for the test to be stopped.

According to the result of the MWT tests, two subjects were eliminated from the driving tests due to their abnormal behavior. Thus, driving tests were conducted with 17 subjects. The test protocols were approved by the Ethics Committee of the Cognitive Science and Technologies Council (Grant No. 1307). Protocols were according to the Declaration of Helsinki.

Signal processing: The EEG data were collected from 6 channels: C3, C4, P3, P4, O1, and O2 channels and Cz as reference channel. The EEG data had low signal-to-noise ratio. The Grubbs' outlier test checked EEG data for outliers. After removing outliers, a 4th-order zero-lag Butterworth band-pass filter (at 0.1-31 Hz) was used to remove out-of-band noise resulting and the power line interferences; the frequency of the power line interferences was 50 Hz. Furthermore, other physiological signals such as electrocardiography (ECG), electromyography (EMG), and

EOG made artifact on EEG signal. Independent component analysis (ICA) is an efficient method for removing artifacts from EEG signal (24).

After normalization, the DWT was applied for decomposing the EEG signals. DWT is an extremely effective time-frequency method for analyzing non-stationary EEG signals. The wavelet transform exploits a multiresolution signal decomposition approach. The DWT creates a series of approximation components using a set of high-pass filters (mother wavelet) and low-pass filters (mirror version). The coefficients of these filters are the DWT basis functions. In the DWT, the family of wavelets are:

$$\Psi_{j,k}(t) = 2^{-\frac{j}{2}}\Psi(2^{-j}t - k), \quad (2)$$

where k is sampling rate and j is resolution.

The scaling coefficients $A_x(j,k)$ (approximations) and the wavelet coefficients $D_x(j,k)$ (details) of the signal x can be derived based on following equations:

$$A_x(j+1,k) = \sum_n h(n-2k)A_x(j,n) \quad (3)$$

$$D_x(j+1,k) = \sum_n g(n-2k)D_x(j,n), \quad (4)$$

where h(n) and g(n) can be viewed as the coefficients of low-pass and high-pass filters, respectively. Figure 4 shows the process of decomposition of EEG signal by using discrete wavelet analysis.

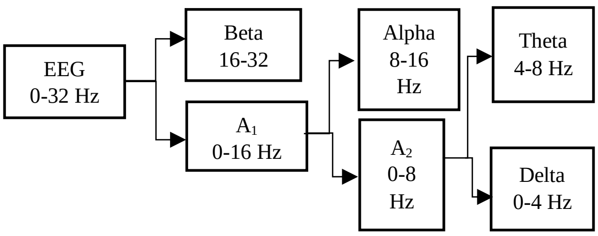


Figure 4. Decomposition of electroencephalography (EEG) signal by using discreet wavelet analysis

In this study, the fourth order Daubechies wavelet family was used for obtaining the DWT coefficients. The window size was set to 30 seconds. By feature extraction of EEG signal, detecting driver's drowsiness in the early stages is possible. In figure 5, the block diagram for our proposed method and its steps are indicated.

Feature selection: In this study, neighborhood component analysis (NCA) was used to reach the highest classification accuracy through feature selection.

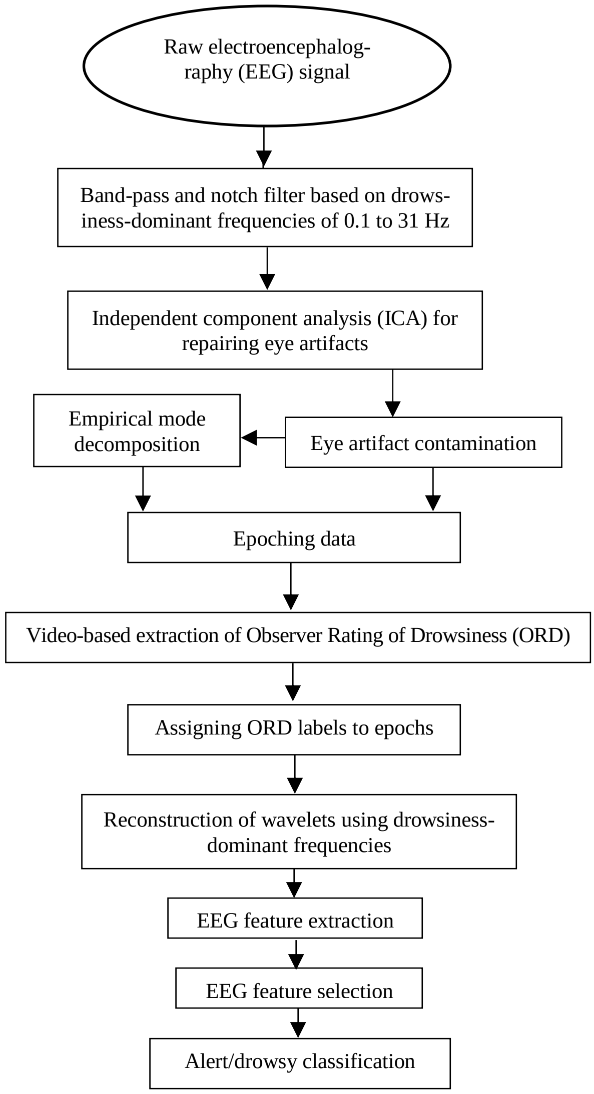


Figure 5. The block diagram for the proposed method and its steps

The training set "T" is as follows: (25)

$$T = \{(x^i, state^i), i = 1,2, \dots n\}, \quad (5)$$

where x^i is vector of features and $state^i$ can be "alert" or "drowsy". The features are: mean, SD, shape factor, root mean square (RMS), range, kurtosis, energy, entropy, and power spectrum for each frequency band (delta, theta, alpha, beta). There is accuracy for classification (25):

$$A(w) = \sum_{i=1}^{n}\sum_{j=1\, j\neq i}^{k} \frac{exp\left(\frac{-F}{\alpha}\right)}{\left(\sum_{j=1}^{m} exp\left(\frac{-F}{\beta}\right)\right)} x_{ij}, \quad (6)$$

where $F(w) = \sum_{k=1}^{m} w_k^2 \left|x_{ik} - x_{jk}\right|$ and w denote the weight of the feature, and

$$x_{ij} = \begin{cases} 1, if\ x_i = x_j \\ 0, otherwise \end{cases}$$

In this method, features with high weights are selected to classify data, and features with low weights are ignored.

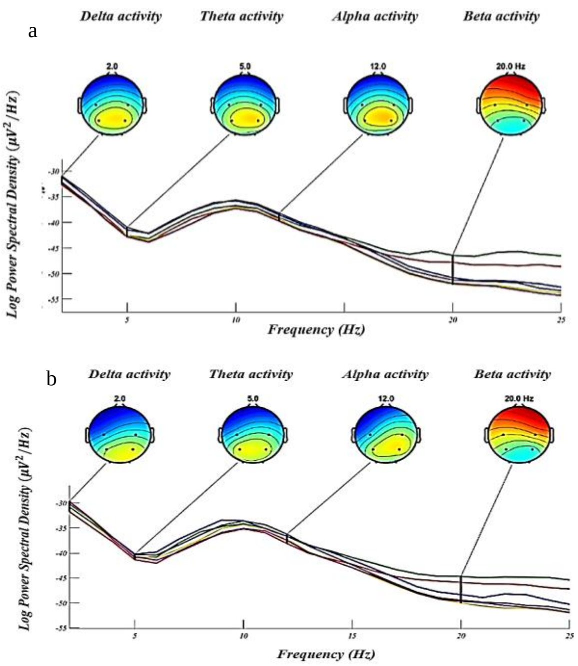


Figure 6. The log-power spectra of delta, theta, alpha, and beta frequency bands for all independent component analysis (ICA) components in (a) alert state, (b) drowsy state

Results

In this study, 19 healthy subjects participated in the VR-based highway-driving experiments. The data of C3, C4, P3, P4, O1, and O2 EEG channels of subjects were used for driver drowsiness detection. The ICA algorithm regardless of scalpel location obtains independent sources from EEG signals. ICA is used to find a linear mapping matrix A for matrix S ($S = [s_1, s_2, \dots, s_N]$) such that X = AS. The log-power spectra of delta, theta, alpha, and beta frequency bands for all ICA components in alert and drowsy states are calculated and indicated in figure 6.

Feature extraction: There are bursts of activity known as alpha spindles that occur at frequencies between 11 and 15 Hz, taking 0.5 to 1.5 seconds. An alpha spindle in the EEG could be used to assess the fatigue and awareness level of drivers (12).

An EEG alpha spindle is indicated in figure 7.

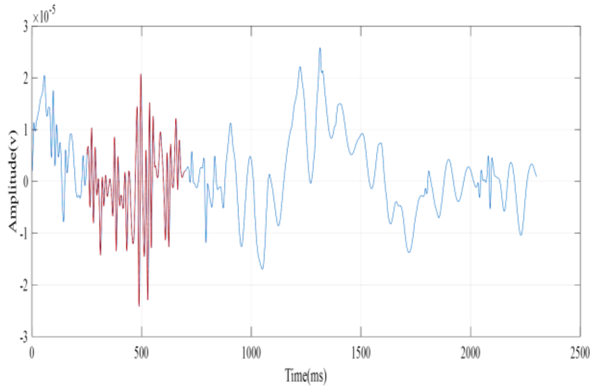


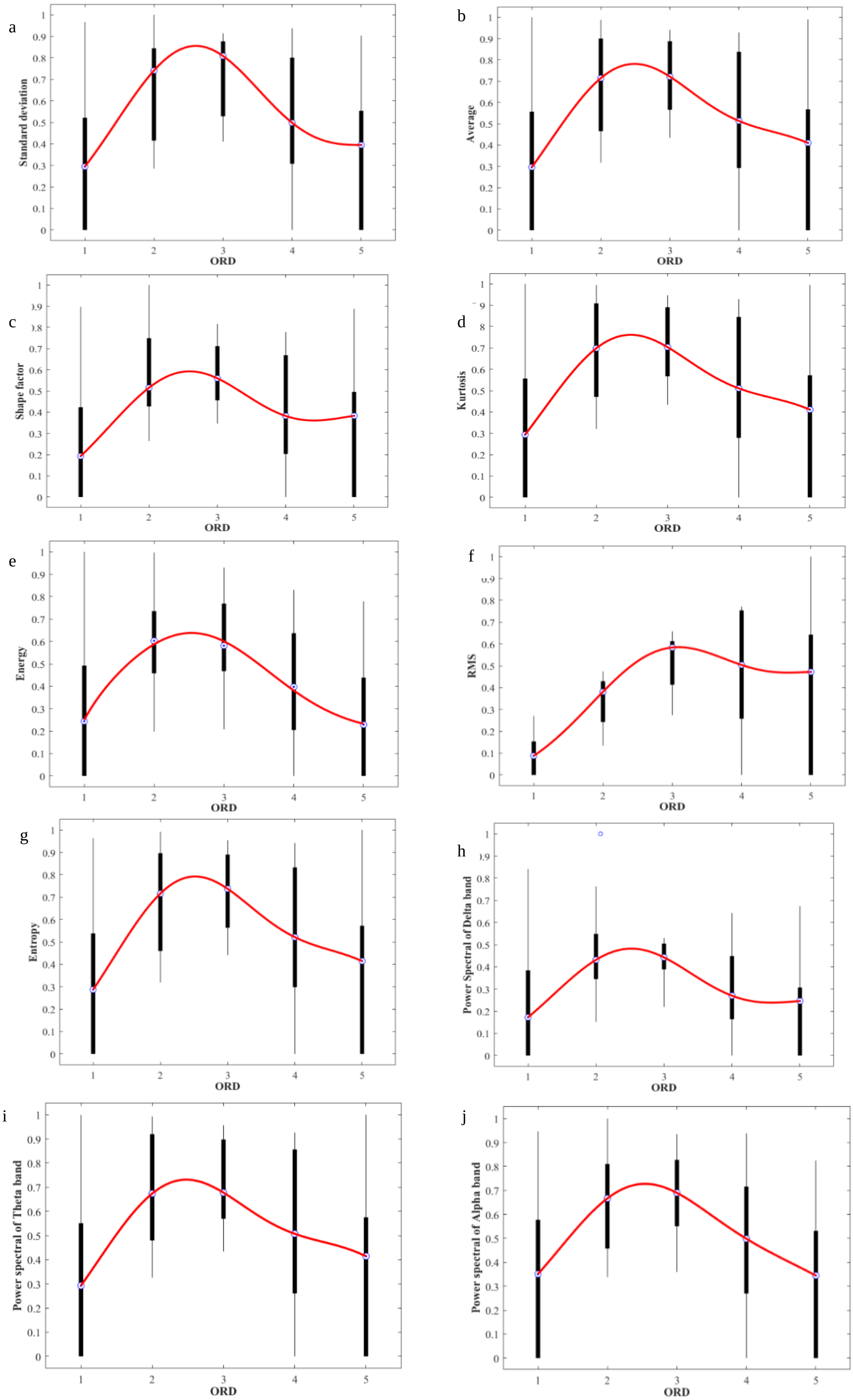
Figure 7. An electroencephalography (EEG) alpha spindle (26)

For driver drowsiness detection, a feature that drastically changes during transition from wake to the early stage of drowsiness is desired. In figure 8, the variations of the features during transition from alertness to drowsiness state are shown. In table 1, the parameters of binormal functions to estimate the features of the EEG signal are indicated.

Table 1. The parameters of binormal functions used to estimate the statistical features of the electroencephalography (EEG) signal

Feature	a_1	b_1	a_2	b_2	c
Mean	0.468	1.222	0.854	-0.402	-0.110
Energy	0.444	-0.297	-34.888	-3.651	0.194
Entropy	0.866	-0.382	0.468	1.242	-0.111
Kurtosis	0.781	-0.372	0.280	0.935	-0.077
RMS	0.628	-0.378	0.250	1.056	0.064
Shape factor	0.658	-0.144	0.165	1.130	0.058
SD	0.464	1.187	0.784	-0.421	-0.093
Power of delta	0.473	1.631	0.601	-0.048	-0.049
Power of theta	0.520	-0.331	0.281	1.603	-0.045
Power of alpha	0.398	1.630	0.880	-0.274	-0.036
Power of beta	0.468	1.221	0.854	-0.402	-0.111
	0.638	-0.299	0.428	1.585	-0.058

SD: Standard deviation; RMS: Root mean square


a
Standard deviation
ORD
b
Average
ORD
c
Shape factor
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d
Kurtosis
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Power spectral of Alpha band
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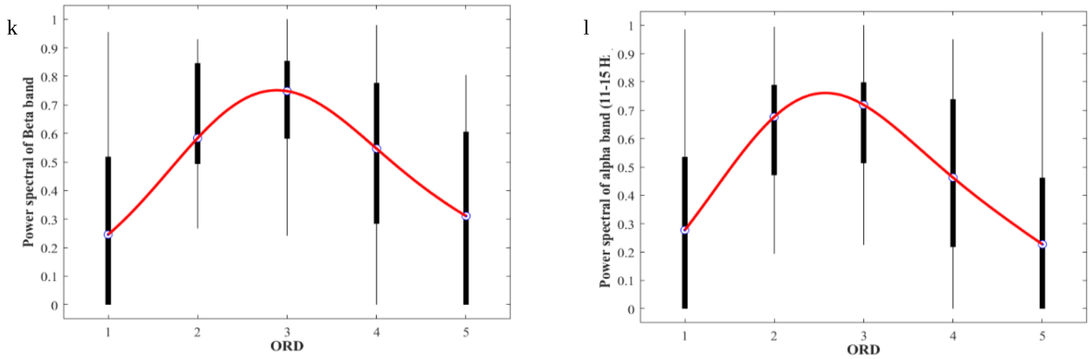

Figure 8. The variation of statistical features during transition from alertness to drowsiness state including (a) mean, (b) standard deviation (SD), (c) shape factor, (d) kurtosis, (e) energy, (f) root mean square (RMS), (g) entropy, power spectral of (h) delta, (i) theta, (j) alpha, (k) beta bands, and power spectral of alpha bands (11-15 Hz) where alpha spindles occur

In this study, NCA method was used for feature selection and the threshold of weights of features was considered equal to 1.5, given that six features including mean, SD, kurtosis, energy, entropy, and power of alpha band in 11-15 Hz (alpha spindle) were selected. In table 2, the weights of the features are indicated.

Classification: The extracted features including mean, SD, kurtosis, energy, and entropy are served as the inputs to the KNN, SVM, classification trees, and Naive Bayes classifiers. 70%, 15%, and 15% of the data for each subject were used as training, testing, and validation data, respectively. The potential of single channel P4 for driver drowsiness detection is proved (26, 27). In addition, as shown in figure 6, most alpha waves emit from channel P4, given that two methods were proposed to detect drowsiness. In the first method, driver drowsiness was detected based on data of C3, C4, P3, P4, O1, and O2 channels. In the second method, only data of single channel P4 was used for drowsiness detection and the results were compared together. In table 3, the classification results of all channels for each subject are indicated. In table 4, the classification result of single-channel P4 for each subject is shown.

Discussion

In this study, EEG features were analyzed and classified to detect driver drowsiness in the early stage of drowsiness. The driver drowsiness detection can be beneficial only if detected in the early stage such as the ORD level of 2.5, when there is an enough time to prevent extreme drowsiness and its consequences such as fatal crashes. 6 features including mean, SD, kurtosis, energy, entropy, and power of alpha band in 11-15 Hz drastically changed in the early stage of drowsiness in comparison to their amounts in the alertness state. These features are fed into the several types of classifiers. Among these classifiers, classification tree has the highest performance of 93% by using a single-channel P4 data and 88% by using data of all channels (C3, C4, P3, P4, O1, O2).

Several features made this study unique, and it hardly can be compared with other studies, such as analyzing data based on ORD. However, we compared it with some studies in field of drowsiness detection. In table 5, the results of this study were compared to some strong and reliable studies in the field of drowsiness detection.

As shown in table 5, this study achieved high performance in detecting early drowsiness, especially the result of using single-channel P4 is entirely desirable.

The main application of this article is to detect driver drowsiness based on single-channel P4.

Table 2. The features and their computed weights

Features and their weights					
SD	1.75	Entropy	1.59	Power of theta	1.37
Shape factor	1.05	Mean	1.91	Power of alpha (8-15 Hz)	1.42
RMS	1.39	Energy	1.60	Power of beta band	1.29
Kurtosis	1.76	Power of delta	0.90	Power of alpha 11-15 Hz (spindle)	1.79

SD: Standard deviation; RMS: Root mean square

Table 3. Accuracy of classifiers based on C3, C4, P3, P4, O1, O2 data for each subject

Feature	KNN	SVM	Classification tree	Naive Bayes
S1	79.90	78.20	88.40	85.00
S3	83.77	80.68	89.06	91.37
S4	82.86	87.68	90.29	83.75
S5	80.02	73.84	80.15	76.49
S6	96.33	58.56	100.11	96.33
S7	95.33	88.68	96.81	87.93
S8	79.34	66.59	73.66	49.58
S9	75.92	56.83	74.14	56.60
S10	86.71	65.61	87.57	82.60
S11	73.66	74.09	82.59	79.90
S12	97.36	81.91	97.36	96.59
S13	89.53	89.16	91.32	99.74
S14	98.88	99.38	99.48	98.25
S15	98.28	98.53	97.49	97.24
S16	91.18	77.28	77.28	85.00
S18	98.57	97.97	97.59	97.69
S19	79.90	80.86	82.06	81.62
Ave	87.50	79.76	88.55	85.04

KNN: K-nearest neighbor; SVM: Support vector machine

Using data of a single-channel is very preferable, because of reducing cost, increasing of speed of computation, and being less intrusive for drivers. In addition, a drowsiness detection method based on a single-channel is more practical in real world, because placing several electrodes needs a technical knowledge about channel location and it is a time-consuming process.

Conclusion

In this study, the EEG signals were used for driver drowsiness detection. The EEG data were collected from C3, C4, P3, P4, O1, and O2 channels, and the drowsiness level was measured by the ORD method. 6 features including mean, SD, kurtosis, energy, entropy, and power of alpha band in 11-15 Hz (alpha spindle) were extracted. The result showed that the classification tree had 88.55% and 93.13% accuracy with using data of all channels (C3, C4, P3, P4, O1, O2) and the single-channel P4, respectively. These results show that single-channel P4 has the highest potential to detect drowsiness. Using the data of a single-channel is incredibly preferable in the real-world application.

Table 4. Accuracy of classifiers based on single-channel P4 data for each subject

Feature	KNN	SVM	Classification tree	Naive Bayes
S1	91.81	92.43	97.95	91.51
S3	92.74	95.83	89.64	90.79
S4	85.60	93.44	93.44	93.44
S5	80.88	54.23	87.67	63.87
S6	98.96	98.94	98.97	98.45
S7	90.67	97.48	97.22	90.67
S8	91.71	93.92	93.92	91.71
S9	93.50	42.50	85.00	68.00
S10	76.45	95.32	83.12	53.59
S11	83.30	91.87	96.91	84.15
S12	76.56	76.51	86.85	76.52
S13	97.36	55.62	97.22	78.82
S14	97.85	79.34	98.45	97.44
S15	98.33	99.92	98.11	98.98
S16	98.85	99.85	97.64	98.59
S18	98.25	92.73	83.46	74.18
S19	98.04	99.65	97.70	99.28
Ave	91.23	85.86	93.13	85.29

KNN: K-nearest neighbor; SVM: Support vector machine

Table 5. Some studies in the field of drowsiness detection

References	Method	Classification accuracy (%)
(27)	Linear regression model	86.20
		84.60
(28)	LDA, KNN, and SVM	87.50
(29)	Neural networks	87.40
(30)	CCNN	86.08
(31)	Clustered group SVM, SVM, and RBFNN	88.70
		84.30
This study	KNN, classification trees, Naive Bayes, SVM	88.55
		93.13

LDA: Linear discriminant analysis; KNN: K-nearest neighbor; SVM: Support vector machine; CCNN: Channel-wise convolutional neural network; RBFNN: Radial basis function neural network

In-ear EEG device is a wireless device that can be used for future studies to collect data of P4 channel, because P4 is located fairly near the ear. In addition, there are other EEG wireless devices which can be used in future to detect driver drowsiness based on single-channel P4.

Conflict of Interests

Authors have no conflict of interests.

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