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Comparison among driving state prediction models for car-following condition based on EEG and driving features

Liu Yang[a], Wei Guan[b,*], Rui Ma[c], Xiaomeng Li[d]

[a] School of Transportation, Wuhan University of Technology, Wuhan 430063, China

[b] Key Laboratory of Transport Industry of Big Data Application Technologies for Comprehensive Transport, Ministry of Transport, Beijing Jiaotong University, Beijing 100044, China

[c] Department of Civil and Environmental Engineering, University of Alabama in Huntsville, Huntsville, AL 35899, USA

[d] Centre for Accident Research and Road Safety-Queensland (CARRS-Q), Institute of Health and Biomedical Innovation (IHBI), Queensland University of Technology (QUT), Kelvin Grove 4059, Australia

A R T I C L E I N F O

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A B S T R A C T

Risky driving states such as aggressive driving and unstable driving are the cause of many traffic accidents. Many studies have used either driving data or physiological data such as electroencephalography (EEG) to estimate and monitor driving states. However, few studies made comparison among those driving-feature-based, EEG-feature-based and hybrid-feature-based (combination of driving features and EEG features) models. Further, limited types of EEG features have been extracted and investigated in the existing studies. To fill these research gaps aforementioned, this study adopts two EEG analysis techniques (i.e., independent component analysis and brain source localization), two signal processing methods (i.e., power spectrum analysis and wavelets analysis) to extract twelve kinds of EEG features for the short-term driving state prediction. The prediction performance of driving features, EEG features and hybrid features of them was evaluated and compared. The results indicated that EEG-based model has better performance than driving-data-based model (i.e., 83.84% versus 71.59%) and the integrated model of driving features and the full brain regions features extracted by wavelet analysis outperforms other types of features with the highest accuracy of 86.27%.

1. Introduction

Road traffic accidents have been a great threaten to human's safety. As reported by National Highway Traffic Safety Administration (NHTSA), there were 35,092 motor vehicle traffic fatalities in the United States in 2015. Many accidents were caused by risky driving states, such as aggressive driving and unstable driving. Therefore, the prediction of drivers' driving states is quite necessary to improve road safety.

In recent decades, two kinds of data sources have been widely used to estimate and predict drivers' driving states. One is the driving data collecting from detection sensors of vehicles and the other is the driver physiological data such as EEG signals. Quintero et al. (2012) developed a driver behavior classification model using vehicle position, speed, acceleration and steering angle from GPS data, which can estimate whether a driver was aggressive or moderate. Chen et al. (2015) extracted common features from vehicle motion data to detect four kinds of drowsy/distracted driving states. Amata et al. (2009) collected real-world driving data including steering and brake information to predict the pedal operation patterns at unsignalized intersections with the highest accuracy of 70%. Aljaafreh et al. (2012) proposed a Fuzzy logic-based driving style recognition system using acceleration and speed parameters to categorize driving style into below normal, normal, aggressive and very aggressive. Wang et al. (2010) conducted an on-road experiment to collect both longitudinal and lateral driving data and used K-means to classify the driving behaviors into five groups.

Compared with driving state prediction from driving data, driver physiological data, especially EEG signals, can reveal more information related to drivers' cognitive state and also have potentials to achieve short-time estimation and prediction (Hajinoroozi et al., 2016; Sun et al., 2015; Lin et al., 2007). Chuang et al. (2015) proposed an EEG-based perceptual function integration system to predict drivers' four levels of vigilance state. Dahal et al. (2014) applied time varying autoregressive analysis on EEG data to distinguish distracted driving from normal driving. Pastor et al. (2006) conducted a real driving experiment and confirmed the positive correlations between alertness (indicated by EEG data) and driving behavior (indicated by the frequency of mirror-gazing). Wan et al. (2016) used EEG wavelet features and

* Corresponding author.

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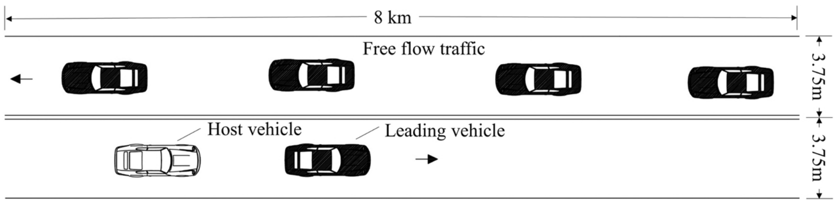


Fig. 1. The road alignment and driving scenario.

ROC curve analysis to classify driving anger into four levels and the highest accuracy was 80.21%. In addition, numbers of studies have used EEG to detect and monitor drivers' drowsiness or fatigue (Raut and Kulkarni, 2014; Garcés Correa et al., 2014; Zhao et al., 2011).

Although many studies have used either driving data or physiological parameters to estimate driver states, there still remains some unsolved research problems: (1) those studies mainly focused on driver states with high risks such as fatigue, drowsiness or distraction, while the driving states under normal driving condition were seldom considered. (2) The EEG analysis methods were quite simplex and limited types of EEG features were extracted and investigated in the existing studies. (3) Few studies compared the prediction performance of different kinds of prediction models. To bridge the gaps, this study first explored two EEG analysis techniques and two signal processing methods to extract twelve kinds of EEG features. Then, the comprehensive comparison of driving state prediction performance among different types of features, including EEG features, driving behavior features and hybrid features of both EEG and driving behavior features, were discussed. The essence of driving state prediction is similar to a classification problem, which aims at distinguishing different types of driving states (Hajinoroozi et al., 2016). Therefore, the selection of critical features that can distinguish various kinds of driving state is of great importance. This study used EEG data and driving behavior data collected from our previous experiment (Yang et al., 2018b). The objectives of this paper are: (1) a thoroughly study of EEG feature extraction methods and (2) comparing the performance among driving-feature-based, EEG-based and hybrid-feature-based driving state prediction models.

The remaining part of the paper is organized as follows. Section 2 introduces the simulated driving experiment, data collection and five types of driving states. In Section 3, the extraction approaches of multiple input features for predicting driving states are elaborated. Section 4 presents the results of each type of feature-based driving state prediction model. In Section 5, the prediction performance of driving-data-based, EEG-based and hybrid-feature-based models is compared and discussed. Finally, the conclusions of this research are demonstrated in Section 6.

2. Experiment and material

2.1. Participants

Fifty-seven healthy adult participants with normal or corrected to normal vision were recruited for the driving experiment. However, five participants were excluded from analyses due to simulator motion sickness. Thus 52 participants (27 males, 25 females) aged between 26 and 50 years old (mean = 35 years; standard deviation = 7 years) completed the experiments successfully. Each participant held a valid driver's license and their average driving experience was 10 years with a standard deviation of 7 years. All the participants were in good health and claimed no medications used in the 24 hours prior to the experiment.

2.2. Driving scenario and experimental procedure

A two-lane straight road scenario was constructed without any intersections or cross-traffic. The total length of the road was 8 km with 3.75 m lane width. The road was edged by urban landscape, including buildings such as banks, supermarkets and office buildings. The speed limit was 80 km/h. The driving task was an ordinary car-following task in the daytime with a leading vehicle driving ahead of the simulator. The leading vehicle was controlled to perform several accelerations and decelerations, and the traffic flow also changed from a free flow condition to a congested flow condition. By such design, we aimed to stimulate the different driving states of drivers (e.g. stable and aggressive driving states). To establish a real-world driving environment, a free flow traffic was set on the opposite lane. The road alignment and driving scenario are shown in Fig. 1.

Upon arrival, all participants read and signed the written informed consent form for the experiment. Next, they were introduced the requirements of the experiment. For example, they were asked to behave as they normally drove under the traffic rules. Then, an approximate 10 minutes practice drive in the simulator was performed by each participant to get acclimated to the simulated driving operations. Finally, each participant completed the formal car-following simulated driving. The time duration for the experiment was about 15 minutes and the 10-minute EEG and driving behavior data of steady car-following stage were used for further analyses.

2.3. Data collection

2.3.1. EEG data

EEG data were acquired using a 64-channel Neuroscan system with 1000 Hz sampling rate. The 64 channels included 62 channels of EEG signals and 2 reference channels. Then, the EEG data were preprocessed to remove artifacts. The detailed preprocessing steps were as follows: (1) the raw data were re-sampled down to 512 Hz to simplify data process (Kim et al., 2015); (2) a zero-phase finite impulse response filter with cutoff frequencies of 0.5 Hz and 30 Hz was utilized to remove noises (Kar et al., 2010); (3) data channels were rejected based on channel statistics (Delorme et al., 2006); (4) the artifacts were automatically removed by ADJUST plugin (Mognon et al., 2011); (5) channels were re-interpolated by simple average method; (6) re-reference and baseline correction. This preprocessing strategy is a basic and universally applicable strategy suggested by Mognon et al. (2011). Each step has its specific effects and we only remove artifacts including blinks, eye movements and generic discontinuities by ADJUST, so that the important EEG information are reserved as much as possible.

2.3.2. Driving data

A high-fidelity driving simulator with one degree of freedom at Beijing Jiaotong University (BJTU) was used to conduct the experiment and collect driving data. Fourteen initial driving behavior variables were extracted from the raw simulator data (60 Hz), which reflected three aspects of driving performance: (1) vehicles' longitudinal and lateral movements (5 variables): longitudinal and lateral acceleration (m/s^2), head deviation (°), lateral lane deviation (m), distance to the road center line (m); (2) vehicles' operations (6 variables): degree of acceleration pedal (°), force of brake pedal (N), acceleration and deceleration (m/s^2), steering wheel angle (°), speed (m/s); (3) relations between the simulator and the leading vehicle (3 variables): space headway (m), time headway (s), relative speed (m/s).

2.4. Driving behavior states

Up to date, many studies have used either driving data or EEG data to estimate driver status such as drowsiness or distraction (Daza et al., 2011; Li et al., 2017b; Chuang et al., 2015; Wang et al., 2015). It has been confirmed that driver's mental status is closely related to specific frequencies of EEG components (e.g. delta, theta, alpha and beta waves) (Almahasneh et al., 2014; Chai et al., 2017).

In this study, we were keen to investigate the potential of EEG in predicting different driving behavioral status in a common driving situation such as normal car-following. Driving aggressiveness and stability were regarded as two main aspects in evaluating driving states under ordinary driving conditions (Wang et al., 2010). In addition, it should be noted that different from the concept of "aggressive drivers" that may involve traffic violation behaviors and a particular driving style, the aggressive driving state in this paper described more of the drivers' present driving status that could be influenced by the traffic conditions and reflected by multiple behavioral variables (e.g. large accelerations and lateral deviations).

With the use of K-means clustering, five types of driving behavior states were identified, which were aggressive-stable state, unaggressive-stable state, unaggressive-unstable state, aggressive-unstable state and normal state. From original driving data to the five driving states, the main procedure (Yang et al., 2018b) is as follows: (1) Data processing. The initial driving behavior variables were classified by K-means, which representing driving style and stability respectively (namely aggressive versus unaggressive, stable versus unstable). (2) Feature selection and extraction. With the use of support vector machine and support vector machine recursive feature elimination (Guyon et al., 2002), two driving behavior features, i.e., driving style feature and driving stability feature, were extracted. (3) Clustering. Again, K-means was used to classify five types of driving behavior states with the driving style feature and driving stability feature as the inputs. In addition, both EEG raw data and initial driving behavior variables were treated in an equivalent manner and weighed equally during the whole data processing stage.

3. Driving state prediction using multiple inputs

With the assumption that EEG relates to driving aggressiveness and stability, we investigated various EEG analysis methods for the extraction of driving states related EEG features. Then, driving-data based, EEG-based and hybrid-feature-based driving state prediction models were modified from the driving behavior recognition model in Yang et al. (2018b) with three major improvements.

Firstly, the model was modified from same-time recognition to short-term prediction. The same-time recognition described a simultaneous connection of driving data and EEG data, while the short-term prediction described the impact of EEG at an earlier stage on the later-stage driving state. Such sequential connection implies a potential causal relationship that a same-time recognition method cannot reveal. Though short-term prediction, it implies that driving state information is able to be acquired in advance, and thus offers the chance for the driver assistance systems to intervene in cases when a risky state (either aggressive or unstable state) is detected. As for the selection of prediction time interval, after several repeated trials, it was found that the prediction time interval of 60 s (with the accuracy of 83.84%) was more effective than 10 s and 30 s (with the accuracy of 82.45% and 81.25% respectively), so the time interval was set 60 s for the present condition. In addition, we restrained our study within scenarios where the traffic condition is stable without obvious variations, such as the sudden brake of the front vehicle. It should be noted as well that the time interval is adjustable according to different driving conditions. Since the selected length of data was 10 minutes, except the first 1 minute, the remaining 9 minutes periods were utilized to evaluate the prediction performance.

Secondly, more types of input features were considered in the present model. Specifically, various EEG features extraction methods, including power spectrum analysis, wavelets analysis and brain source localization technique were used to extract 12 types of EEG features. As for the driving features, namely the driving style feature and driving stability feature indicating driver aggressiveness and stability, were derived from the mean values and the standard deviations of the initial driving behavior variables. Furthermore, the novel hybrid features combining both EEG and driving data were also studied.

Thirdly, since the EEG signals were not generated right under each electrode, but from the underlying cortical sources. Instead of using simple division of EEG channels, we used brain source localization technique and k-means to extract and classify the underlying cortical sources. Finally, six driving-related brain sources were obtained.

3.1. Driving state prediction from EEG data

EEG data collected on a specific electrode are actually generated by a mixture of underlying brain source signals, rather than the brain area exactly under the electrode (Onton et al., 2006; Zhao et al., 2015). Therefore, the recorded EEG signals are multi-source signals, and it is also the reason for the highly correlated adjacent channels data. In addition to the original multi-channel EEG data, more and more researchers have successfully used independent component analysis (ICA) to obtain discriminative information in the forms of independent component activations (ICs) or different brain regions (BRs) to estimate driving performance, such as driver's cognitive performance and distraction (Hajinoroozi et al., 2016; Wang et al., 2014). By running ICA decomposition, ICs on time domain were obtained. Then, component clustering was performed to classify different brain regions.

Power spectrum analysis by fast Fourier transformation (FFT) (Zhao and He, 2013; Cooley et al., 1969) and wavelets analysis by wavelet packet transform (WPT) (Kar et al., 2010; Wali et al., 2013) are two common signal processing methods to extract frequency domain features of EEG. In this study, both FFT and WPT were adopted to extract the final EEG features, which are the amplitude (A), log-transformed power (LTP) and power spectral density (PSD) of the four EEG waves (i.e., δ-wave (0.5–3 Hz), θ-wave (4–7 Hz), α-wave (8–13 Hz) and β-wave (14–30 Hz)) for power spectrum analysis and the energy (E), relative energy (RE) and entropy (SE) for wavelet analysis.

Finally, twelve kinds of EEG features (i.e., 3 ICs FFT features, 3 ICs WPT features, 3 BRs FFT features and 3 BRs WPT features) were extracted and examined through the driving behavior prediction method. The schematic diagram for EEG feature extraction is shown in Fig. 2.

3.2. EEG analysis methods

3.2.1. ICA

ICA is a linear decomposition method that can separate multi-source data into statistical independent data. It is a kind of blind source separation and has been widely used in EEG studies to remove artifacts and extract independent components for various applications (Castellanos and Makarov, 2006; Lin et al., 2005). The objective of ICA is to find a 'linear mapping matrix or unmixing matrix' to make the

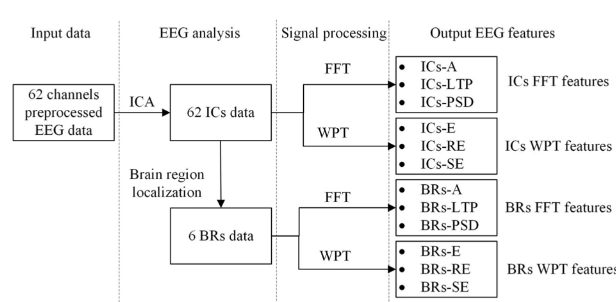


Fig. 2. The schematic diagram for EEG feature extraction.

linear transformed components statistically independent (Lin et al., 2005). The ICA model (Onton et al., 2006) can be formulated as:

$$U_i(t) = WX_i(t) \tag{1}$$

where X is the original multi-channel EEG data, which is a matrix of n channels by t time points; W is the 'unmixing matrix' and U is the ICs on time courses. Then, the back projection of ICs was preformed as follows:

$$X_i(t) = W^{-1}U_i(t) \tag{2}$$

where the inverse matrix W^{-1} is the 'mixing matrix', representing the relative weights of each component project to the original multi-channel EEG data.

In this study, the ICA was preformed by EEGLAB function pop_runica to produce the maximally temporally independent components. Since the original EEG data were collected by 62 channels, then 62 ICs were obtained for each participant.

3.2.2. Brain region localization

Previous studies found that the frontal, central, parietal, temporal, somatomotor and occipital regions on cerebral cortex are related to driving behaviors (Yang et al., 2018a; Chuang et al., 2015). Therefore, these six brain regions were selected as the component clusters of interest in this study.

After applying ICA, EEGLAB plugin-in DIPFIT2 was utilized to fit single dipole source models for each participant. K-means was used to classify all the ICs according to the dipole source models and power spectra derived for each IC. Components with 3 standard deviations from any of the cluster centroids were recognized as "outlier" cluster. Then, 18 clusters were obtained referring to the study of Brooks and Kerick (2015). Finally, clusters of the frontal, central, parietal, temporal, somatomotor and occipital regions were selected for further analyses, as shown in Fig. 3.

3.2.3. EEG feature extraction by FFT

Power spectrum analysis has been widely used for EEG feature extraction. In this study, the periodogram method using FFT (Zhao and He, 2013) was used to transform the ICs data and BRs data from time domain to frequency domain. Then, the amplitude, log-transformed power and power spectral density of δ-wave, θ-wave, α-wave and β-wave were extracted as 3 FFT features.

3.2.4. EEG feature extraction by WPT

Wavelet transform is the most common time-frequency method for EEG studies, which can provide a transformed EEG data to represent both time and frequency domains (Wang et al., 2015). WPT was adopted in this study to decompose the ICs data and BRs data into a series of subspaces that have different frequency band using a specific wavelet function. According to the study of Kar et al. (2010), dB4 (Daubechies family) was selected since it was the most appropriate wavelet function for EEG signals. Then, the signals were decomposed into six levels. At level six, the wavelet coefficients of frequency bands contained δ-wave, θ-wave, α-wave and β-wave were extracted. Finally, the energy, relative energy and the wavelet entropy (Shannon's entropy) of wave j, $j \in [1, 4]$ were calculated as follows (Kar et al., 2010):

$$E_j = \sum_{k=1}^{L} [C_j(k)]^2 \tag{3}$$

$$p_j = \frac{E_j}{\sum_j E_j} \tag{4}$$

$$\mathrm{SE} = -\sum_j p_j .\ \log(p_j) \tag{5}$$

where E_j, p_j and SE represent the energy, relative energy and Shannon's entropy of wave j respectively. $C_j(k)$ is the k-th wavelet coefficient of wave j and L indicates the total number of wavelet coefficient of wave j.

3.3. Driving state prediction from driving data

Most prevailing studies have used driving data, such as vehicle speed, acceleration, to classify or model driving behaviors (Zhang et al., 2016; Constantinescu et al., 2010; Chen et al., 2013). In this study, driving style feature and driving stability feature extracted from the mean values and standard deviations of the 14 initial driving behavior variables were utilized as the input driving features to predict driving behavior states.

3.4. Driving state prediction from combinations of EEG and driving data

Based on the comparison results of the prediction performance among different EEG features, the EEG features with the highest accuracy would be selected as the final EEG input features. Then, the combinations of the final EEG input data and driving data were adopted as the inputs for the hybrid-feature-based driving state prediction.

4. Results

In this study, all the data processing and the machine learning algorithms were conducted by Matlab 2014a and EEGLAB toolbox. The final driving state prediction was implemented by KNN algorithm and a leave-one-subject-out cross validation was adopted for validation. Five indices derived from the confusion matrix were used to evaluate the performance of driving state prediction models, which were accuracy, precision, sensitivity, specificity, F1 score. For multi-class confusion matrix, it is a $k \times k$ matrix whose cells a_{ij}, i, $j \in [1, k]$ indicate frequencies of samples with true class C_i and predictive class C_j.

Then, indices for evaluating classification performance are formulated as:

$$\text{Accuracy} = \sum_{j=1}^{k} a_{\mathrm{jj}} / \sum_{i=1}^{k} \sum_{j=1}^{k} a_{\mathrm{ij}} \tag{6}$$

$$\text{Precision}(i) = a_{\mathrm{ii}} / \sum_{j=1}^{k} a_{\mathrm{ij}} \tag{7}$$

$$\text{Sensitivity}(i) = a_{\mathrm{ii}} / \sum_{i=1}^{k} a_{\mathrm{ij}} \tag{8}$$

$$\text{Specificity}(i) = \left(\sum_{j=1}^{k} a_{\mathrm{jj}} - a_{\mathrm{ii}}\right) / \left(\sum_{i=1}^{k} \sum_{j=1}^{k} a_{\mathrm{ij}} - \sum_{j=1}^{k} a_{\mathrm{ij}}\right) \tag{9}$$

$$F1\text{score} = \frac{2\text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \tag{10}$$

where accuracy is the probability that a sample has been correctly classified (Alberg et al., 2004). For class i, precision indicates the proportion of samples in predictive class C_i that are classified correctly; sensitivity, which also named recall, is the ratio of samples in true class C_i that are classified correctly; specificity represents the probability that samples in true class except C_i (namely in true negative class) that are correctly classified; F1 score is the combination of precision and recall (Ruuska et al., 2018). The five indices range from 0 to 1, and higher value represents better performance. Accuracy is an overall index for model evaluation, while others are used to measure the specific characteristics for each class. In order to evaluate the prediction models sufficiently, the precision, sensitivity, recall and F1 score were averaged for all classes and then utilized as overall indices.

In addition, for driving state prediction based on BRs data, only 21 participants provided the whole six brain regions data and one brain region may contain more than one component for a single participant. Then, the actual sample size for prediction was equal to the number of participants with complete brain regions data and the power or energy data in case of more than one component in one brain region were

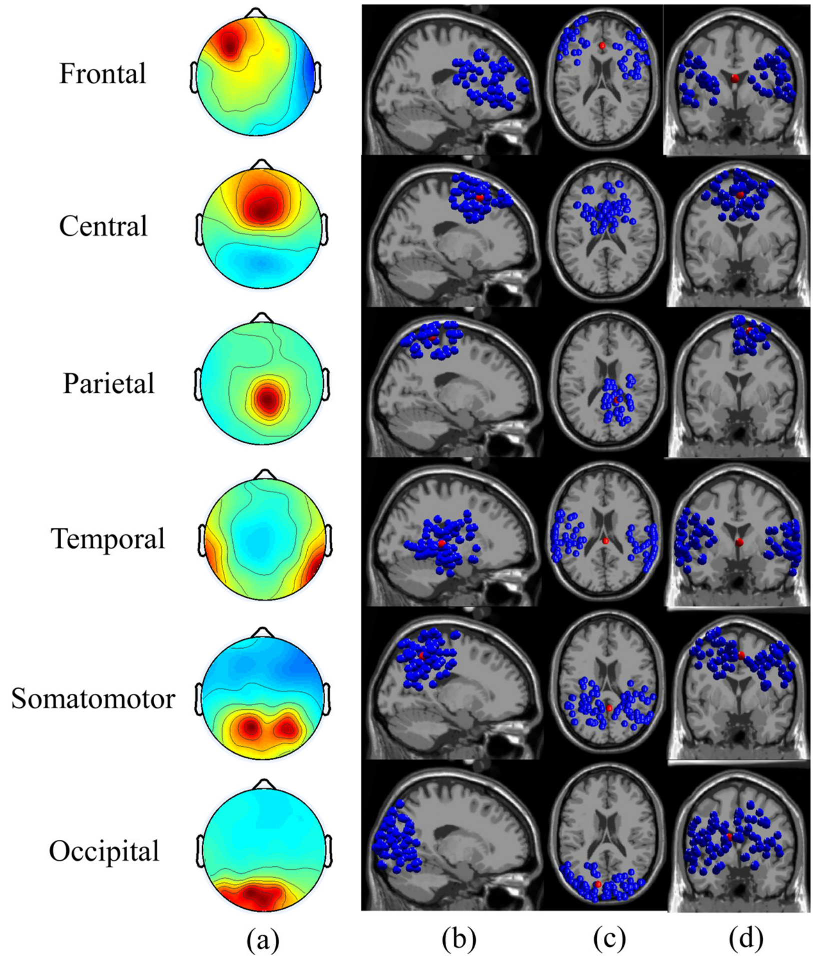


Fig. 3. Scalp maps and equivalent dipole source localization of six brain regions. (a) Scalp maps for each brain region; (b) sagittal plane; (c) horizontal plane; (d) coronal plane. Each blue spot refers to an independent component for each participant and the red spot is the average position across participants.

calculated by simple averaging approach (Chuang et al., 2015).

4.1. ICs-based prediction results

The three FFT features (i.e., A, LTP and PSD) and three WPT features (i.e., E, RE and SE) for each IC were extracted as the EEG features. Thus, there were six different prediction models which had different input features (i.e., ICs-A/E, ICs-LTP/RE, ICs-PSD/SE). We first examined these ICs-based prediction models and Fig. 4 presents the results. As shown in Fig. 4, both FFT features and WPT features have similar variation tendency and ICs-LTP, ICs-PSD, ICs-RE and ICs-SE have better performance than ICs-A and ICs-E with all the five indices over 60%. Hence, LTP, PSD were selected as effective FFT features and RE, SE were selected as effective WPT features for further analyses.

4.2. BRs-based prediction results

Instead of directly using total ICs features as the inputs, BRs features with specific regional information would probably contribute to more precise results in driving state prediction. The effective FFT features and WPT features were calculated integrally (i.e., all six BRs) or separately (i.e., each single BR) as the inputs. Finally, a total of 14 types of BRs features were extracted, including full brain regions, frontal, central, parietal, temporal, somatomotor and occipital FFT/WPT features. As shown in Fig. 5, the results indicated that the full brain region features significantly outperform any other single brain region features and the full brain region WPT features have the best performance with 83.85% accuracy with all other indices over 80%.

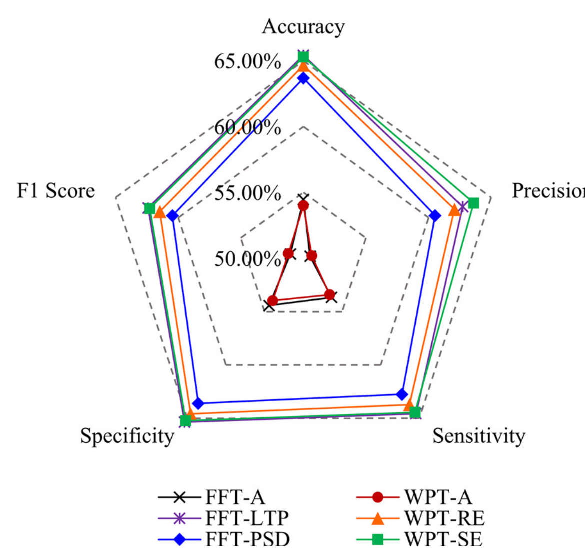


Fig. 4. The performance indices of ICs-based models.

4.3. Prediction results of EEG combining driving data

Compared with ICs-based prediction, BRs-based prediction has better performance. Thus, we explored the performance of the combinations of BRs features in full brain regions and driving behavior features as the inputs. The prediction performance of driving-data-only

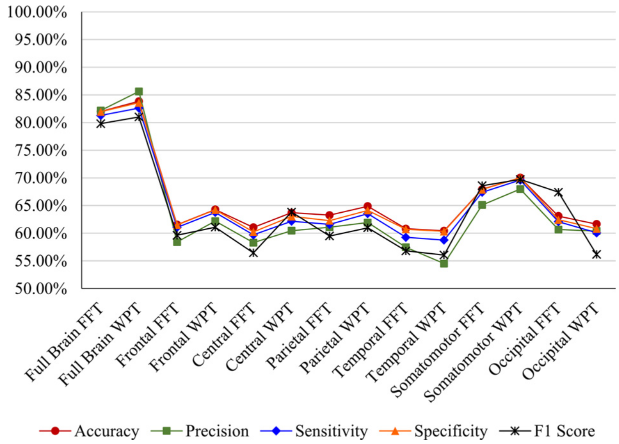
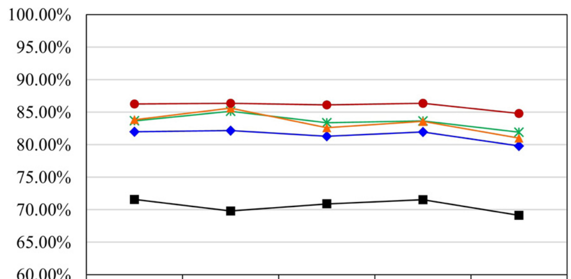


Fig. 5. The performance indices of BRs-based models.



	Accuracy	Precision	Sensitivity	Specificity	F1 Score
Dri-only	71.59%	69.81%	70.90%	71.53%	69.13%
FFT-only	82.00%	82.17%	81.29%	81.94%	79.81%
Dri-FFT	83.67%	85.13%	83.38%	83.64%	81.92%
WPT-only	83.84%	85.62%	82.61%	83.59%	81.01%
Dri-WPT	86.27%	86.35%	86.13%	86.36%	84.80%

Fig. 6. The comparison of driving-data-based, EEG-based and hybrid-feature-based driving state prediction.

(Dri-only), full brain regions' FFT features (FFT-only) and WPT features (WPT-only), and the combinations of full brain regions' FFT/WPT data and driving data (Dri-FFT/WPT) was compared. The results are shown in Fig. 6. It can be seen from Fig. 6 that the difference of accuracy between FFT-only and Dri-FFT is small, but all the performance indices of Dri-FFT are higher than those of FFT-only. Additionally, the figure also demonstrates that the Dri-WPT outperforms the FFT/WPT-only and Dri-only with higher values in all performance indices. This indicates that the classification performance of hybrid features is superior to the EEG features, followed by the driving features.

5. Discussion

In this study, we concentrated on the investigation of various EEG analysis methods and the comparison of prediction performance among multiple input features including different EEG features (i.e., ICs features and BRs features extracted by FFT or WPT), driving features and hybrid features of both EEG data and driving data. Each type of input features corresponds to a prediction model. Five indices including accuracy, precision, sensitivity, specificity and F1 score were used to evaluate the prediction performance of each test model.

5.1. ICs-based analysis

Six ICs features (i.e., ICs-A, ICs-LTP, ICs-PSD, ICs-E, ICs-RE, ICs-SE) were examined. The results indicated that the prediction performance of ICs-LTP/PSD and ICs-RE/SE was better than that of ICs-A and ICs-E; accordingly, among all ICs-based FFT features and WPT features, LTP/PSD features and RE/SE features were supposed to be more relevant to the driving states. Because the amplitude or energy of each brain wave differs greatly and has multiplicative effects, thus transformation forms such as LTP/PSD and RE/SE are more commonly used in the EEG studies (Lin et al., 2005; Hajinoroozi et al., 2015; Kar et al., 2010; Li et al., 2017a).

5.2. BRs-based analysis

Different brain regions deal with different physiological functions: the frontal region is mainly responsible for conducting executive functions; the central and parietal regions are related to human's sensory activities; the temporal region deals with auditory tasks; the somatomotor region is associated with motor control and the occipital region is involved with visual information reception (Chuang et al., 2015; Yang et al., 2018a). Hence, BRs-based analysis can facilitate the investigation of intrinsic correlation mechanism between brain regions and driving states. The BRs-based results showed that features extracted from full brain regions outperform any other features extracted from single brain region, with all the performance indices over 80%. This finding is consistent with Chuang et al. (2015), which suggests the integration network of full brain regions for driver's vigilance state identification achieved the highest accuracy when comparing with single brain source. Among the six brain regions, the somatomotor region outperformed the rest of brain regions. Therefore, the driving behavior state classified by vehicle operation data was more relevant to the somatomotor region which may coordinate drivers' vehicle control activities.

Additionally, the highest accuracy of BRs features (i.e., BRs-WPT features extracted from the full brain regions) reached 83.85%, which is significantly higher than the best result of ICs features with the highest accuracy of 65.40%. It indicates that too much redundant information were included in ICs features which may offset and weaken the effective information (Wang et al., 2014). Therefore, selecting effective components and classifying spatial brain sources are of great importance to improve the performance of the driving state prediction model.

5.3. Comparison among prediction models using multiple inputs

Totally three kinds of prediction results were compared, which were driving-data-based prediction, EEG-based prediction and prediction of hybrid features. Considering that BRs features outperform ICs features, the full brain regions FFT features and WPT features were selected for EEG-based prediction and hybrid-feature-based prediction. The combinations of driving behavior features and BRs-WPT features achieved best prediction performance (accuracy = 86.27%, precision = 86.35%, sensitivity = 86.13%, sensitivity = 86.36%, F1 score = 84.80%), followed by EEG-based features (accuracy = 83.84%, precision = 85.62%, sensitivity = 82.61%, specificity = 83.59%, F1 score = 81.01%) and driving-data-based features (accuracy = 71.59%, precision = 59.81%, sensitivity = 70.90%, specificity = 71.53%, F1 score = 69.13%). This result indicates that the EEG-based model outperforms the driving-data-based model with an increasing accuracy of 12.26%. In addition, comparing with either driving-data-based model or EEG-based model, the hybrid-feature-based model improves the driving state prediction performance in a comprehensive way, with all evaluation indices reaching the highest. Hence, it can be concluded that EEG data contain important information related to the driving states. Additionally, the driving data, which were directly collected from vehicle operation process, still have the advantages in reflecting drivers' operation conditions, and could be used as a good complementary data source for driving state prediction.

One of the limitations of the current work is that the baseline and predictive data were both collected from a single drive since the sample size is too small to separate training set and testing set. A larger sample size and field test data are suggested in the future research to further validate the present results. Another limitation is related to the driving scenario, which tends to be idealized as it excludes the variations in the real-world car- following situation.

6. Conclusions

Since limited types of EEG features were extracted and investigated in the existing studies and few studies made comparisons among different types of feature-based driving state prediction methods under normal steady traffic condition. Our major contribution is to fill those gaps and compare the prediction performance of different input features. In this study, we developed several short-term driving state prediction models by using drivers' EEG features and/or driving features as the inputs. Various EEG feature extraction methods including two EEG analysis techniques (i.e., ICA analysis and brain source localization), two signal process methods (i.e., power spectrum analysis by FFT and wavelets analysis by WPT) and six types of features (i.e., A, LTP, PSD and E, RE, SE) were investigated and compared. It is innovative to compare the prediction performance of driving state prediction models with multiple inputs including EEG features, driving features and hybrid features of them. It was found that: (1) among the six types of features, LTP/PSD and RE/SE are more effective than A/E features. (2) The somatomotor region was found to have better predictive ability than other single brain source from the six brain regions, thus it may be more relevant to the driving states. (3) Full brain region features have better prediction performance than any single brain region features and also outperform the ICs features. (4) The hybrid features of BRs-WPT features and driving features achieve the best classification result with the average accuracy of 86.27%. In addition, as for signal process methods, power spectrum analysis and wavelets analysis have similar results but generally wavelets analysis has slightly better performance.

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