

Driving Fatigue Detection with Fusion of EEG and Forehead EOG

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Abstract—In this paper, we fuse EEG and forehead EOG to detect drivers' fatigue level by using discriminative graph regularized extreme learning machine (GELM). Twenty-one healthy subjects including twelve men and nine women participate in our driving simulation experiments. Two fusion strategies are adopted: feature level fusion (FLF) and decision level fusion (DLF). PERCLOS (the percentage of eye closure) is calculated by using the eye movement data recorded by eye tracking glasses as the indicator of drivers' fatigue level. The prediction correlation coefficient and root mean square error (RMSE) between the estimated fatigue level and the real fatigue level are both used to evaluate the performance of single modality and fusion modality. A comparative study on modality performance is conducted between GELM and support vector machine (SVM). The experimental results show that fusion modality can improve the performance of driving fatigue detection with a higher prediction correlation coefficient and a lower RMSE value in comparison with solely using EEG or forehead EOG. And FLF achieves better performance than DLF. GELM is more suitable for driving fatigue detection than SVM. Moreover, feature level fusion with GELM achieves the best performance with the prediction correlation coefficient of 0.8080 and the RMSE value of 0.0712 on average.

I. INTRODUCTION

The driving fatigue remains to be one of the important factors that lead to traffic accidents [1] [2]. According to the study of the National Highway Traffic Safety Administration (NHTSA) of USA and Virginia Tech Transportation Institute (VTTI), nearly 80 percent of crashes and 65 percent of near-crashes involved some of driver inattention [3] [4]. Thus, to develop a system that actively monitors the driver's fatigue level in real time and produces alarm signals when necessary, is essential to prevent accidents [1].

A critical issue that a fatigue detection system must address is how to accurately detect driving fatigue in real time. In the last decades, various driving fatigue detection methods have been proposed [5] [4]. According to the sensors used, those methods can be categorized into three classes: video based approach, multi-sensor based approach, and physiological signals based approach. However, both video based methods and multi-sensor based approaches are hard to be used to predict driving fatigue in advance. The existing studies indicate that

physiological signals are relatively fast and direct reflection of fatigue.

There are various studies on driving fatigue detection with physiological signals. Among these signals, electroencephalogram (EEG) is considered to be the most direct, effective, and promising one to detect driving fatigue [6]. EEG provides an objective, functional mapping of brain activity on the scale of seconds. Shi *et al.* proposed several vigilance estimation models based on EEG [7] [8] [9] [10]. Their work and results have demonstrated that EEG-based methods are effective to detect vigilance. By analyzing the EEG changes in fatigued subjects while performing a simulated driving task, Eoh *et al.* found that EEG α , β , β/α and $(\alpha + \theta)/\beta$ indices showed significant differences between driving periods [2]. Lin *et al.* developed a drowsiness-estimation system based on EEG by using independent component analysis (ICA) [11]. Electrooculogram (EOG) is another commonly studied physiological signal in various researches. Bulling *et al.* investigated eye movement analysis as a promising sensing modality for activity recognition with Electrooculography (EOG) [12]. Many studies found relations between features extracted from EOG and fatigue, drowsiness or vigilance. Ma *et al.* extracted EOG features, mainly slow eye movements (SEM), to detect subjects' vigilance level during a monotonous task [6]. Morris *et al.* extracted specific components of eye and eyelid movement from EOG and found that blink rate was the best predictor of performance decrements resulting from pilot fatigue [13]. To be convenient for practical applications, Zhang *et al.* proposed a novel electrode placement on forehead to record EOG signals and extracted features from forehead EOG to detect driving fatigue [14].

Since EEG or forehead EOG only focuses on a certain specific aspect and the driver's fatigue level only can be inferred from the information available [1], it is difficult to build a robust fatigue detection model by using single modality. Golz *et al.* pointed out that the most promising approach for detecting driving fatigue or drowsiness is based on fusion of multiple electrophysiological signals with soft computing manner [15]. Yang *et al.* concluded that more features, especially the contact physiological features, which cover more features implying driving fatigue recognition,

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are favorable for inferring driving fatigue more reliably and accurately [1]. Thus, to be convenient for practical applications and improve the performance and robustness of the model simultaneously, we fuse EEG and forehead EOG to detect driving fatigue. There are various data fusion strategies like signal level fusion, feature level fusion and decision level fusion, which all can be applied to biosignals [15]. In this paper, we focus on feature level fusion and decision level fusion strategies.

At feature level, classical serial feature fusion is a common used strategy in many data fusion studies. Based on serial feature fusion, Golz *et al.* introduced a combination of linear and nonlinear methods for feature fusion for the detection of sudden and non-anticipated lapses of attention in car drivers due to drowsiness [15]. For decision level fusion, multi-classifier or multi-expert combination strategies are also widely used in recent years. Lu *et al.* compared different decision level fusion strategies and feature level fusion strategy by combining eye movements and EEG to enhance emotion recognition [16]. Considering that we are dealing with a regression problem, we adopt serial feature fusion and decision level fusion with mean rule in this study, in which the mean of two regression outcomes is used as the final prediction value.

In our driving simulation experiments, instead of manually labelling the driving fatigue level by the subjects' self-report, we use the method proposed by Gao *et al.* [17] to label the drivers' fatigue level automatically using PERCLOS during the driving process with the SMI eye tracking glasses. PERCLOS denotes the percentage of eyelid closure over the pupil over time and reflects slow eyelid closures ("droops") rather than blinks. PERCLOS is considered to be the most reliable and valid determination of a driver's alertness level [17], which can be calculated by using the eye movement data recorded by eye tracking glasses. The eye tracking glasses is a wearable device and is more efficient than traditional video cameras [14] [17].

In this paper, we explore efficient EEG features and use the approach proposed by Zhang *et al.* [14] to extract features from forehead EOG and traditional EOG, and take advantage of their complementary information for driving fatigue detection with two different fusion strategies. We also compare the performance of forehead EOG with traditional EOG. The experimental results show that forehead EOG can achieve good performance as traditional EOG for driving fatigue detection, and the fusion of EEG and forehead EOG yields higher prediction correlation coefficient and lower RMSE (root mean square error) value in comparison with single modalities. We also conduct a comparative study on modality performance between GELM and SVM. The experimental results demonstrate that GELM is more suitable for driving fatigue detection than SVM. And feature level fusion by using GELM achieves the best performance for detecting driving fatigue.

II. METHODS

A. Data Preprocessing

Twenty-one sets of experimental data which are collected during our driving simulation experiments are used in this

paper. 900 samples are obtained in each experiment, of which 720 samples are used as a training set and the rest 180 samples are used as a testing set. To reduce the computational complexity, we down-sample both EEG and EOG signals to 200 Hz, and then a bandpass filter between 0 and 60 Hz for EEG signals and a bandpass filter between 0 and 30 Hz for EOG signals are applied to reduce the noise and remove the artifacts.

B. Feature Extraction

1) *EOG Signals*: To maintain the statistical significance of EOG [6], we extract features from a fixed 8 s non-overlapping window in our research.

For traditional EOG, we use simple subtraction method to extract horizon electrooculogram (HEO) and vertical electrooculogram (VEO) from EOG signals. For forehead EOG, we utilize the approach proposed by Zhang *et al.* [14] to extract horizon electrooculogram (HEO) and vertical electrooculogram (VEO) in our study. FastICA from EEGLAB toolbox [18] is adopted to extract forehead VEO. According to the description of Zhang *et al.* [14], forehead HEO extracted by using FastICA sometimes has a negative correlation with traditional HEO. Thus, we use a simple but more robust subtraction method to acquire forehead HEO [14].

For both traditional EOG and forehead EOG, we utilize the wavelet method and the peak detection algorithm to extract EOG features about blink, fixation, and saccade. The wavelet transform method is used to compute continuous wavelet coefficients at scale 8 with a Mexican mother wavelet. Then we perform the peak detection algorithm provided by MATLAB on the wavelet coefficients to detect the blink and saccade. For the simplicity of extracting features from EOG, we only detect the blink from extracted VEO and the saccade from extracted HEO. The blink or saccade duration is detected as fixation. Then the mean, maximum, variance, and derivative of blink, fixation, and saccade are calculated. After excluding some features whose correlation coefficients with PERCLOS are under a certain threshold, we finally select 36 features of blink, fixation, and saccade to be used to establish the detection model. The moving average filter is used to smooth the features, which can reduce the influences of artifacts and the components of small correlation with fatigue. And then we perform the normalization to scale the features to the range [0, 1]. Table I represents the finally selected 36 features.

TABLE I
THE FEATURES EXTRACTED FROM EOG

Group	Features
saccade	maximum/minimum/mean of saccade rate/saccade amplitude maximum/mean of saccade rate variance/saccade amplitude variance power/mean power of saccade amplitude saccade number
blink	mean/maximum of blink rate variance/amplitude variance maximum/minimum/mean of blink amplitude power/mean power of blink amplitude maximum/mean/sum of blink rate blink number
fixation	mean/maximum of blink duration variance/saccade duration variance maximum/minimum/mean of blink duration/saccade duration

2) *EEG Signals*: According to the work of Shi *et al.* [8] [9], we only use 12 EEG channels (CP1, CPZ, CP2, P1, PZ, P2, PO3, POZ, PO4, O1, OZ, and O2) as key brain areas to detect driving fatigue.

Two effective EEG features, power spectral density (PSD) and differential entropy (DE), are extracted and compared in this study. PSD is widely used in EEG signal analysis and high related with fatigue and drowsiness. According to the statement of Shi *et al.* [9], DE is equivalent to the logarithm PSD and also high related to vigilance. The whole frequency band of the features distributed from 1 Hz to 50 Hz is divided into five frequency bands: delta (1-4 Hz), theta(4-8 Hz), alpha (8-14 Hz), beta (14-31 Hz), and gamma (31-50 Hz).

Short-term Fourier transform (STFT) with a 8s non-overlapping window is used to compute the power spectral density and differential entropy in each frequency band. A linear dynamic system (LDS) with the window length 1 minute is performed to smooth the feature sequence to make the features more stable [10], which can reduce the influence of artifacts after feature extraction. Then, normalization is performed to scale the EEG features to the range [0, 1].

Since the electrode CPZ is too close to the reference electrode, it often causes short circuit between them. Thus, only the EEG data recorded by the other 11 EEG electrodes are used in this study. And the total dimension of EEG features for a sample of 11 electrodes is 55.

C. Calculating PERCLOS

According to the description of Gao *et al.* [17], PERCLOS can be approximately calculated by the percentage of durations of blinks and ‘CLOS’ (slow eyelid closures or long-time closures) over a specified time interval. The specific formula of PERCLOS is defined as

$$PERCLOS = \frac{blink + CLOS}{interval} \quad (1)$$

$$interval = blink + fixation + saccade + CLOS. \quad (2)$$

Eye tracking glasses can record detailed eye movement data based on the videos of subjects’ two eyes, and eye movement data can provide many detailed parameters about fixation, blink and saccade such as durations, start time, and end time.

In this study, PERCLOS is calculated within 60 seconds time window with a 8 seconds moving step, which is consistent with EEG and EOG features. Considering fatigue level is not supposed to vary abruptly during the monotonous task [17], we perform sliding average to smooth the result.

D. Data Partition

Since EEG and EOG features are time dependent [7] [14], we cannot divide the whole data randomly. Considering that the time for different subjects to feel fatigued is different, the whole data should not be divided with some fixed interval [14]. In order to obtain a training model with good performance, the training set should contain both fatigue samples and awake samples. Taking into account several factors mentioned above, we equally divide each subject’s whole data into five segments

with 24 minutes in the chronological order, and one segment is used in prediction, while the rest four segments are used to train the model. We perform five-fold cross-validation to get the mean correlation coefficients and the mean RMSE values.

E. Regression model

In our study, we introduce discriminative graph regularized extreme learning machine (GELM) [19] to estimate the drivers’ fatigue level. Meanwhile, a support vector machine for regression (SVR) is used as the baseline to evaluate the performance of GELM.

Extreme learning machine (ELM) is an efficient and practical single-hidden-layer feedforward neural network. Given a training set, $L = \{(x_i, t_i) | x_i \in \mathbb{R}^d, t_i \in \mathbb{R}^m, i = 1, 2, \dots, N\}$, where $x_i = (x_{i1}, x_{i2}, \dots, x_{id})^T$ and $t_i = (t_{i1}, t_{i2}, \dots, t_{id})^T$. With K hidden nodes and activation function g , an ELM can be modeled in matrix form as

$$\beta^T H = T, \quad (3)$$

where

$$H = \begin{bmatrix} g(w_1 \cdot x_1 + b_1) & \dots & g(w_1 \cdot x_N + b_1) \\ g(w_2 \cdot x_1 + b_2) & \dots & g(w_2 \cdot x_N + b_2) \\ \vdots & \vdots & \vdots \\ g(w_K \cdot x_1 + b_K) & \dots & g(w_K \cdot x_N + b_K) \end{bmatrix}_{K \times N}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \beta_2^T \\ \vdots \\ \beta_K^T \end{bmatrix}_{K \times m}, \quad T = [t_1, t_2, \dots, t_N]_{m \times N},$$

where $w_j = (w_{j1}, w_{j2}, \dots, w_{jd})$ is the input weight vector connecting the j th hidden node with input nodes, $\beta_j = (\beta_{j1}, \beta_{j2}, \dots, \beta_{jm})^T$ is the weight vector connecting the j th hidden node with the output nodes, b_j is the bias of the j th hidden node, and $t_i = (t_{i1}, t_{i2}, \dots, t_{im})^T$ is the network output corresponding to sample x_i . Then the output weight of (3) can be estimated by

$$\tilde{\beta} = \arg \min_{\beta} \|\beta^T H - T\|_2^2 = H^\dagger T, \quad (4)$$

where H^\dagger is the Moore-Penrose generalized inverse of H .

Considering the local consistency of data, GELM for regression was proposed to enforce the output of samples among the k -nearest neighbors of each other to be similar. In GELM model, the distance information is used to construct an adjacent graph and the graph regularization term is formulated to constrain the output weights. Similar to the discriminative analysis, the adjacent matrix is defined as

$$W_{ij} = \begin{cases} e^{-\frac{\|h_i - h_j\|^2}{(2\sigma^2)}} & , \text{if } h_i \text{ and } h_j \text{ are among } k\text{-nearest} \\ & \text{neighbors of each other} \\ 0 & , \text{otherwise,} \end{cases}$$

where $h_i = (g_1(x_i), \dots, g_K(x_i))^T$ and $h_j = (g_1(x_j), \dots, g_K(x_j))^T$ are respectively hidden layer

representations for two input samples x_i and x_j . Suppose a diagonal matrix D with the column sums of W as its entries is defined, then we can compute the graph Laplacian matrix $L = D - W$.

Suppose y_i and y_j are two vectors for h_i and h_j , which are mapped by output weight matrix β , respectively. Since y_i and y_j are similar to each other when h_i and h_j are among k -nearest neighbors of each other, we need to minimize the following objective function,

$$\min \sum_{i,j} \|y_i - y_j\|^2 W_{ij} = Tr(YLY^T), \quad (5)$$

where $Y = \beta^T H$. By incorporating the graph regularization term into conventional ELM model, the objective function of graph regularized Extreme Learning Machine can be formulated as

$$\min_{\beta} \|\beta^T H - T\|_2^2 + \lambda_1 Tr(\beta^T H L H^T \beta) + \lambda_2 \|\beta\|_2^2, \quad (6)$$

where $Tr(\beta^T H L H^T \beta)$ is the graph regularization term, $\|\beta\|_2^2$ is the l_2 -norm regularization term, and λ_1 and λ_2 are regularization parameters to balance the impact of these two terms. Finally, we can obtain the result

$$\beta = (H H^T + \lambda_1 H L H^T + \lambda_2 I)^{-1} H T^T. \quad (7)$$

In this study, we use the LIBSVM package [20] and select radical basis function (RBF) for the SVR model. The ranges of the two main parameters of SVM algorithm, the penalty factor C and the parameter γ of RBF, are set to $[0, 1024]$ and $[0.1, 2]$, respectively. All the points of (C, γ) are tried to find the best training model. All the algorithms used in this study are implemented and run in a Matlab environment.

F. Fusion Strategy

After two regression models on EEG and forehead EOG are trained, different modality fusion strategies are used to combine them. In this study, two fusion strategies are adopted: feature level fusion (FLF) and decision level fusion (DLF). At feature level, the EEG feature vector and forehead EOG feature vector are directly concentrated into a larger feature vector, which will be used as the input to train model. At decision level, the mean of the two regression outcomes will be computed as the final estimated fatigue level.

G. Performance Evaluation

In our study, the prediction correlation coefficient and root mean square error (RMSE) are used to evaluate the performance of different modalities. RMSE between the real fatigue level and the estimated fatigue level is used to represent the accuracy. The smaller the value of RMSE, the more precise the driving fatigue estimation is. The correlation coefficient of the regression curve and the real fatigue level curve ranges from -1 to 1. Higher correlation coefficient indicates higher relevance.



(a) Driving simulation environment



(b) A subject wearing eye tracking glasses

Fig. 1. The driving simulation environment and eye tracking glasses used in the experiment.

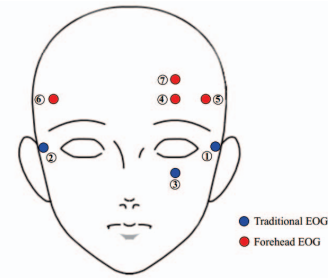


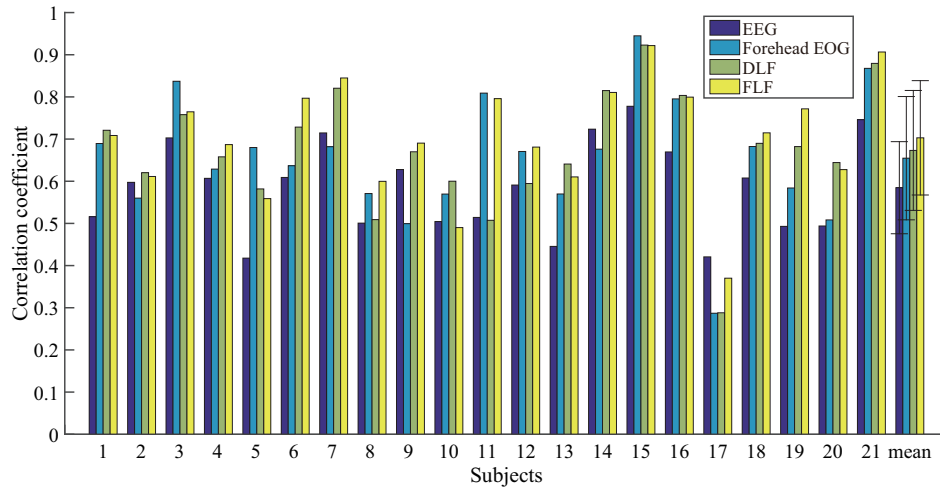
Fig. 2. The electrode placement of forehead EOG and traditional EOG.

III. EXPERIMENT SETUP

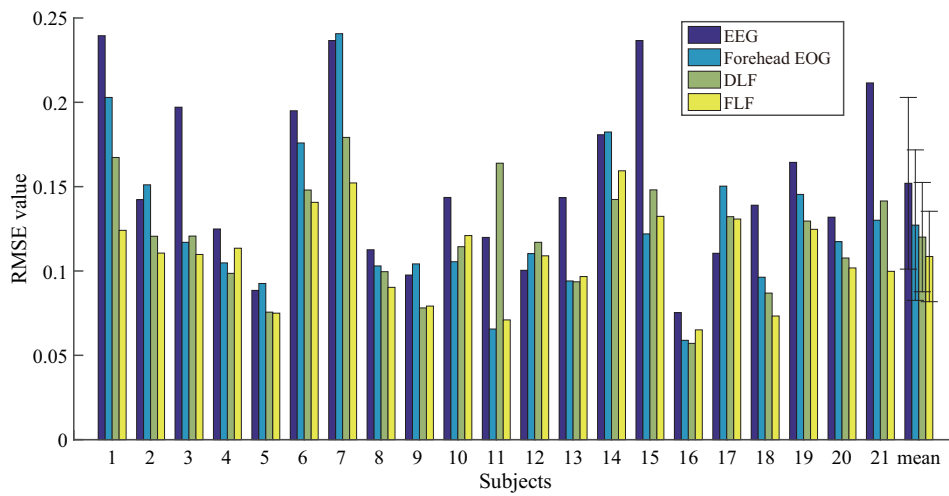
A. Procedure and Subjects

The whole experiment lasted 2 hours and was performed in a car with a driving simulator, which had a four-lane national highway simulating the real road situation. The experiment environment is shown in Fig. 1.

A total of 21 healthy subjects including 12 men and 9 women aged between 20 and 25 participated in our driving simulation experiments. All the subjects were required to have enough sleep at the night before the experiments. For the purpose that the subjects are awake at the beginning of the experiment and fall into sleepy after a period time of driving, all our experiments were conducted after lunch from 13:00 pm to 15:00 pm or after dinner from 21:00 pm to 23:00 pm. Before the experiment started, there was a “warm-up and training” session lasting about 5 min for subjects to be familiar with the vehicle controls. To be able to record real and natural states of the eyes, all the subjects were required to keep their eyes open before they felt tired and do nothing irrelevant with the driving task during our experiments. In order to achieve a better simulation result, subjects as drivers were required



(a) Correlation coefficients of different modalities on all subjects by using SVM



(b) RMSE values of different modalities on all subjects by using SVM

Fig. 3. Performance of two single modalities and two fusion modalities by using SVM.

to keep alertness all the time and try to suppress his/her sleepiness as much as possible to avoid any traffic accident.

B. Data Collection

In our experiments, the electrodes of EEG channels were arranged based on the international 10/20 system and the reference electrode was on the top of the scalp. We adopted the electrode placement of forehead EOG described by Zhang *et al.* [14], and the traditional EOG signals were also recorded as a comparison in this study. We can see the electrode positions of forehead EOG and traditional EOG in Fig. 2. The no. four electrode is the common electrode to both traditional EOG and forehead EOG. The no. five and the no. six electrodes are respectively placed at the edges of forehead, which are at the same height with number four electrode. The no. seven electrode is placed 3cm over the no. four electrode [14].

For each experiment, a total of 12-channel EEG signals and 7-channel EOG signals were recorded by the ESI NeuroScan system at the sampling rate of 1000 Hz and then re-sampled down to 200 Hz for the simplicity of data processing. At the same time, SMI ETG eye tracking glasses was used to record the eye movement data of subjects.

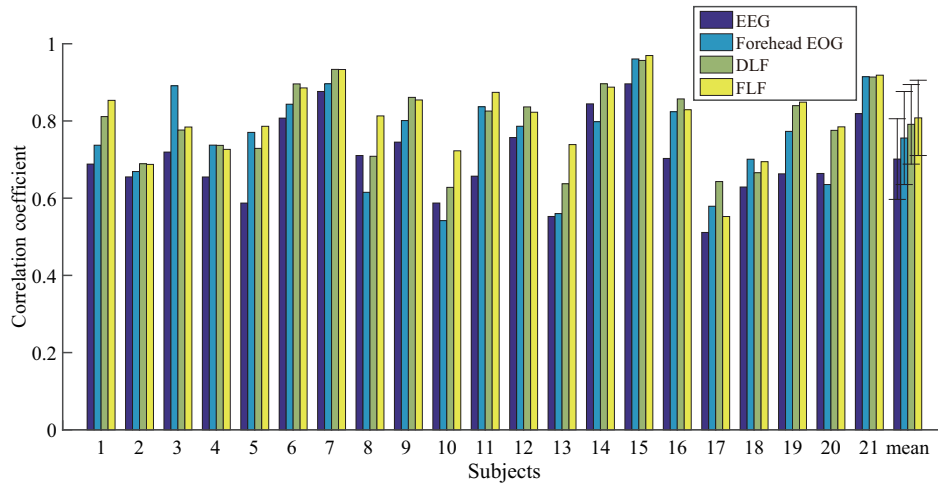
C. Fatigue Measurement

In our experiment, we use the PERCLOS which can be calculated within a time window with a constant width by using the eye movement data recorded by eye tracking glasses as an indicator of drivers' fatigue level.

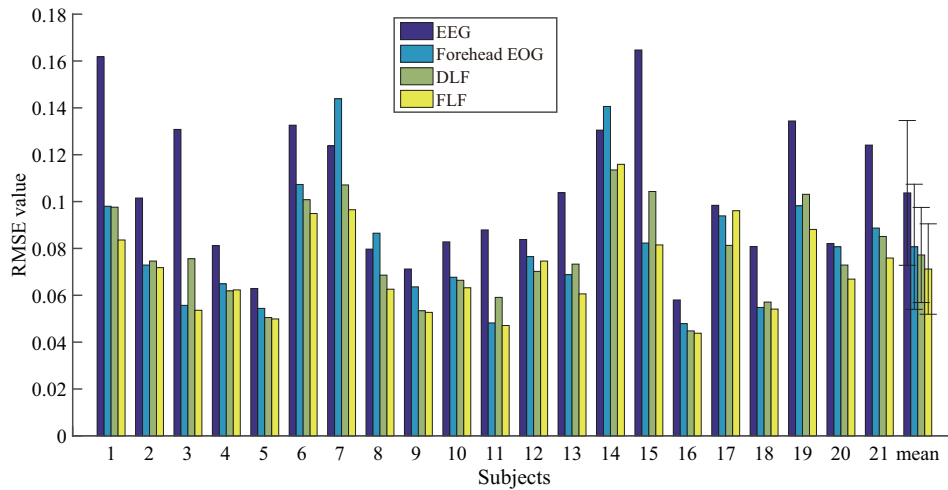
IV. EXPERIMENTAL RESULTS

A. EOG Based Fatigue Detection

Table II shows the mean prediction correlation coefficients and the mean RMSE values of SVM and GELM regression



(a) Correlation coefficients of different modalities on all subjects by using GELM



(b) RMSE values of different modalities on all subjects by using GELM

Fig. 4. Performance of two single modalities and two fusion modalities by using GELM.

TABLE II
THE PERFORMANCE OF TWO DIFFERENT EOGs

Corr	SVM		GELM	
	Traditional	Forehead	Traditional	Forehead
Mean	0.6371	0.6547	0.7623	0.7558
Std.	0.1412	0.1462	0.1241	0.1205
RMSE	SVM		GELM	
	Traditional	Forehead	Traditional	Forehead
Mean	0.1313	0.1272	0.0800	0.0807
Std.	0.0430	0.0446	0.0245	0.0267

models based on traditional EOG and forehead EOG, respectively. As we can see from Table II, GELM has better performance than SVM to detect driving fatigue based on EOG signals. When using the same regression model, forehead EOG has similar prediction correlation coefficient and RMSE value with tradition EOG. This implies that forehead EOG

has good performance as traditional EOG in driving fatigue detection. Besides, when using the same regression model, the corresponding standard deviations of prediction correlation coefficient and RMSE value of two different EOGs are also very similar, which implies that forehead EOG also has good robustness as traditional EOG in driving fatigue detection. Thus, forehead EOG is suitable for driving fatigue detection and more convenient for practical applications than traditional EOG because of its electrode placement on forehead.

B. EEG-Based Driving Fatigue Detection

In this section, we explore efficient EEG features for driving fatigue detection. Table III shows the mean prediction correlation coefficients and mean RMSE values of two EEG features. From the results shown in Table III, we can find that GELM has better performance of EEG-based driving fatigue detection than SVM. By comparing the results of two EEG

TABLE III
THE PERFORMANCE OF TWO DIFFERENT EEG FEATURES

Corr	SVM		GELM	
	PSD	DE	PSD	DE
Mean	0.5001	0.5847	0.6232	0.7013
Std.	0.1302	0.1092	0.1562	0.1045
RMSE	SVM		GELM	
	PSD	DE	PSD	DE
Mean	0.1947	0.1520	0.1253	0.1037
Std.	0.0691	0.0509	0.0342	0.0309

features using same regression model, we can find that DE features achieve higher prediction correlation coefficients and lower RMSE values with smaller standard deviations than PSD features. Thus, regardless of the regression model, the DE features are more suitable for EEG-based driving fatigue detection than the PSD features. Therefore, the DE features of EEG data are chosen to fuse with forehead EOG data.

C. Performance of Modality Fusion

In this section, we fuse forehead EOG data with EEG data to improve the performance of driving fatigue detection. Figs. 3 and 4 show the experiment results of two single modalities and two different modality fusion strategies on all the subjects by using SVM and GELM for regression, respectively. As we can see from the results, the performance obtained by all the models with modality fusion outperforms that based on single modality.

When using SVM for regression, FLF achieves the mean prediction correlation coefficient of 0.7030 which is about 0.12 higher than EEG-based modality and 0.05 higher than forehead EOG-based modality; the mean RMSE value of FLF is 0.1086, which is about 0.043 lower than EEG-based modality and 0.02 lower than forehead EOG-based modality. DLF achieves the mean prediction correlation coefficient of 0.6731 which is higher than two single modalities and the mean RMSE value of 0.1201 which is also lower than two single modalities.

When using GELM for regression, FLF achieves the best performance with mean prediction correlation coefficient of 0.8080, which is about 0.107 higher than EEG-based modality and 0.052 higher than forehead EOG-based modality; the mean RMSE value of FLF is 0.0712, which is about 0.03 lower than EEG-based modality and 0.01 lower than forehead EOG-based modality. DLF can also achieve comparative performance with the mean prediction correlation coefficient of 0.7913 and the mean RMSE value of 0.0772.

Thus, regardless of the training algorithm, the models with modality fusion achieve higher prediction correlation coefficients and lower RMSE values than that of the single modalities, which indicates that modality fusion can combine complementary information in each single modality and effectively improve the performance of driving fatigue detection. Besides, the models with modality fusion achieve smaller standard deviations than that of single modalities, which means modality fusion can also improve the robustness of the model for driving fatigue detection. As we can see that FLF achieves

better performance than DLF, this is because that FLF uses the concentrated feature vectors to train the detection model which takes advantage of more complementary information than DLF.

By comparing the performance of SVM and GELM on each modality, we can see that GELM achieves higher prediction correlation coefficient and lower RMSE value with smaller standard deviations than SVM. This is mainly because that GELM takes the local consistency of data into consideration. Thus, GELM is more suitable for driving fatigue detection than SVM.

Fig. 5 shows the predicting fatigue level curves and the original PERCLOS curves of four different modalities by using GELM, in which the red curves are the predicting results and the black curves are the original PERCLOS values. As we can see, the predicting fatigue level curves of fusion modalities are more consistent with the original fatigue level curve than that of single modalities.

V. CONCLUSION

This paper has shown that fusing forehead EOG data and EEG data can effectively improve the performance of driving fatigue detection. The experimental results on twenty-one subjects indicate that forehead EOG is suitable for driving fatigue detection, which is more convenient for practical applications than traditional EOG. The results of the comparison between two different EEG features show that the DE feature is more accurate and stable than PSD feature for EEG-based driving fatigue detection, which is consistent with the similar conclusion reached by Shi *et al.* [9]. The performance of SVM and GELM on each modality also shows that GELM is more suitable for driving fatigue detection than SVM.

Modality fusion can yield models of higher prediction correlation coefficient and lower RMSE value in comparison with signal modality. When using GELM to train the regression model, FLF strategy achieves the best performance with the prediction correlation coefficient of 0.8080 and the RMSE value of 0.0712 on average, whereas the prediction correlation coefficients of solely using EEG and forehead EOG are respectively 0.7013 and 0.7558, and the RMSE values of two single modalities are respectively 0.1037 and 0.0807. The promising prediction correlation coefficients and RMSE values show the advantages of fusing forehead EOG data and EEG data to detect driving fatigue in future practical applications.

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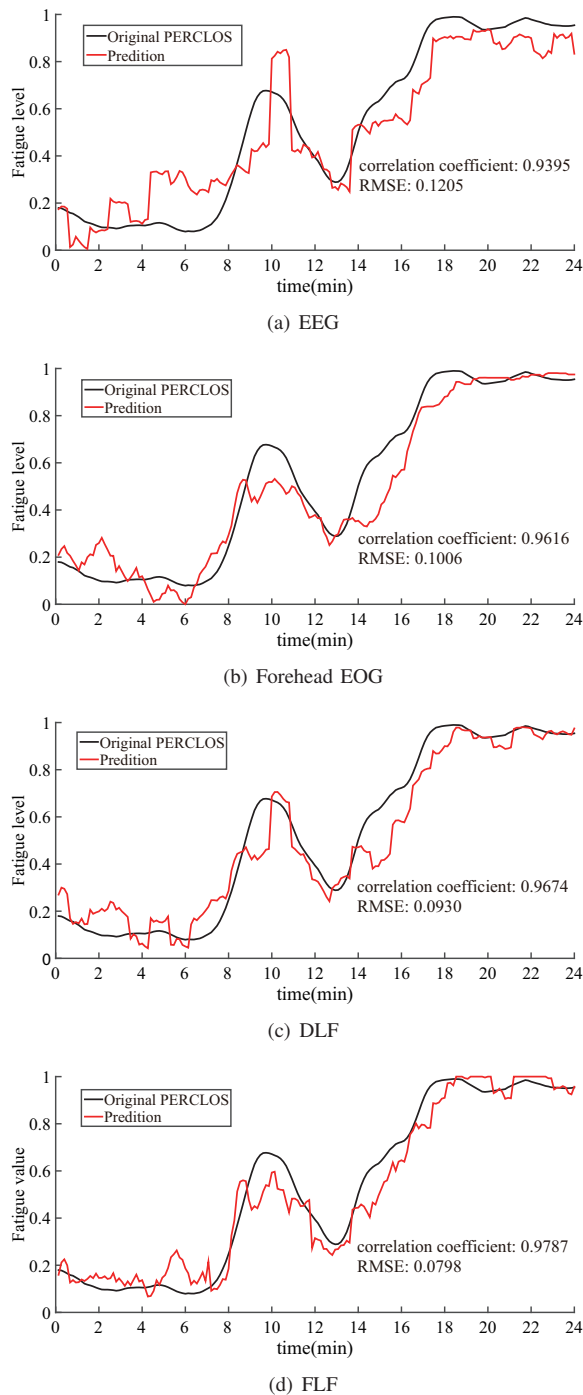


Fig. 5. The predicting fatigue level curves of single modalities and fusion modalities by using GELM

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