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A Novel Approach to Driving Fatigue Detection Using Forehead EOG

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Abstract— **Various studies have shown that the traditional electrooculograms (EOGs) are effective for driving fatigue detection. However, the electrode placement of the traditional EOG recording method is around eyes, which may disturb the subjects' activities, and is not convenient for practical applications. To deal with this problem, we propose a novel electrode placement on forehead and present an effective method to extract horizon electrooculogram (HEO) and vertical electrooculogram (VEO) from forehead EOG. The correlation coefficients between the extracted HEO and VEO and the corresponding traditional HEO and VEO are 0.86 and 0.78, respectively. To alleviate the inconvenience of manually labelling fatigue states, we use the videos recorded by eye tracking glasses to calculate the percentage of eye closure over time, which is a conventional indicator of driving fatigue. We use support vector machine (SVM) for regression analysis and get a rather high prediction correlation coefficient of 0.88 on average.**

I. INTRODUCTION

Physiological signals have been applied to detect driving fatigue in the past decades. Among these signals, electroencephalography (EEG) and EOG are two promising measurements of fatigue [1]. In recent studies, EEG-based methods were extensively applied to driving fatigue detection [2] [3]. In comparison with that of EEG, the amplitude of EOG is significantly higher, which makes EOG more robust to noise than EEG. Two critical issues of EOG-based methods for driving fatigue detection have been investigated recently: one is the electrode placement to record EOG, and the other is how to conveniently label fatigue states. This paper proposes novel approaches to dealing with these two problems.

In traditional EOG-based experiments, EOG signals are recorded by two pair of electrodes on opposite sides of eyes [4]. It is difficult to cover these positions with a wearable device. Therefore, to develop a new electrode placement for recording EOG signals is important for improving the user experience during experiment and practical applications. In this study, we present a novel electrode placement on forehead. For fully making use of existing powerful methods to extract features from traditional EOG, we introduce an effective approach to extracting forehead HEO and forehead VEO.

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In driving simulation experiments of previous studies, the driving fatigue state is usually provided by the subjects' self-report or by manually labelling according to the recorded videos, which is inconvenient for a long time experiment. In this study, we introduce a novel method for automatically labelling the fatigue state during the driving process with SMI eye tracking glasses. The percentage of eye closure over time (PERCLOS) has been proved to be a good indicator of driving fatigue [5]. The existing methods for calculating PERCLOS are not robust in practical applications due to the complexity of eye detection. The eye tracking glasses is a wearable device and can directly record the state of eyes without extra work on eye detection, which is more efficient than traditional cameras [6]. PERCLOS is usually calculated with a 60 seconds window, which makes it not suitable for real-time driving fatigue detection. Besides, the portable device which can accurately track the eye movements is usually too expensive[7]. Therefore, the PERCLOS data obtained from eye tracking glasses is only used as labels in training model stage. In practical application, the well-trained model can be adopted to predict fatigue states.

II. EXPERIMENTS

A. Procedure and Subjects

The whole experiment was performed on a driving simulator, which had a four-lane national highway simulating the real situation. Total seven-channel EOG signals were recorded by the NeuroScan system at a sampling rate of 500 Hz, which then were down-sampled to 125 Hz. A bandpass filter between 0 and 30 Hz was used to eliminate noise signals during the recoding process. At the same time, eye tracking glasses was used to record the videos of subjects' eyes. The experiment environment is shown in Fig. 1.

Our driving simulation experiments were carried out by 14 subjects, including 10 men and 4 women aged around 22. All the subjects were healthy and no wound on the forehead and face. All of them had an afternoon nap habit or went to bed early than 11:30 pm. They were required to keep eye open before they were tired and do nothing irrelevant with the driving task. The mean period of the experiment was about 2 hours for the purpose of insuring the subject to fall into a sleepy state during driving. The time of our experiments contained two periods, one from 12:30 am to 14:30 pm, and the other from 9:30 pm to 11:30 pm.

B. Forehead EOG and Fatigue Measurement

The EOG-based human-machine interfaces have been extensively investigated, and there are plenty of methods to extract features from traditional EOG signals. Compared

(a) Driving simulation system (b) A subject wearing eye tracking glasses

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

with finding new methods to directly extract features from forehead EOG, it is more valuable to find effective methods to separate HEO and VEO from forehead EOG, which is a mixed signal.

Following our previous work [8], we designed a novel placement to extract forehead EOG signals. Fig. 2 shows the electrode positions of both forehead and traditional EOGs in our experiment. The fourth electrode is a common electrode to both forehead and traditional EOGs. The reference electrode is placed at the left mastoid and the ground electrode is placed at the right mastoid. Number five and number six electrodes are respectively placed at the edge of forehead, and at the same height with number four electrode. Number seven electrode is placed 3cm over the number four electrode.

The PERCLOS, which is calculated from the infra-red videos recorded by eye tracking glasses, was chosen to be the indicator of driving fatigue in this study.

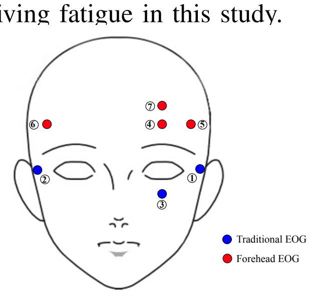

Fig. 2. Electrode placement for traditional and forehead EOG recording

III. METHODS

A. Forehead HEO and VEO Extraction

By extracting HEO and VEO signals from different combinations of signals recorded by forehead electrodes, we found an effective method to extract them from forehead EOG. The correlation coefficients between traditional EOG and extracted EOG were used to evaluate the extraction method. The EOG signals recorded by the fourth and seventh electrodes were used to extract VEO by FASTICA [9]. The two separated signals obtained by FASTICA contained the signal with high similarity to VEO, and it appeared in the first channel.

When the same method was performed on the signals recorded by fifth and sixth electrodes to extract HEO, it got a result of nearly the same correlation with direct subtraction of them. The channel of the extracted HEO in these two separated signals did not appear so fixed. The most similar signal sometimes showed a negative correlation with traditional HEO. Therefore, a simple but more robust subtraction method was finally chosen to acquire forehead HEO. After the EOG being extracted, a median filter was used to remove the noise. Fig. 3 shows the comparison of a segment from one subject between traditional EOG and forehead EOG. The upper part is the traditional EOG, while the lower part is forehead EOG. From Fig. 3, we can see that the amplitude of forehead VEO extracted by FASTICA is significant lower than that of traditional VEO.

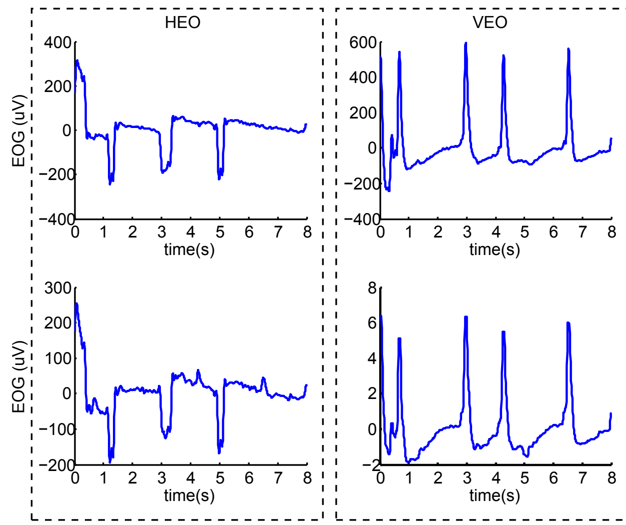

Fig. 3. Comparison of a segment between traditional EOG and forehead EOG

B. Feature Extraction and Smoothing

The wavelet methods have been used in EOG features extraction [4], [10]. As the wavelet transform is sensitive to singularity, it obtains a better result than the derivative method in detecting blink and saccade. We computed the continuous wavelet coefficients at scale 8 with a Mexican mother wavelet. Based on the previous studies, we introduced the peak detection algorithm provided by MATLAB to improve the performance of former threshold-based detection algorithm [4]. The peak detection algorithm was performed on the wavelet coefficients to detect the blink and saccade.

Fig. 4 shows a segment of saccade detection. The green points are the positive peaks, and the blue points are the negative peaks obtained by peak detection algorithm. The peaks with a low threshold amplitude have been ignored. We coded the negative and positive peaks into sequences, in which the positive peak was coded into ‘1’, and the negative was coded into ‘0’. The segment with a ‘01’ or ‘10’ subsequence was chosen as a candidate saccade segment. We can get a straight line from the start point to the end point of the candidate segment. We calculated the slope value of the line and the correlation between the line and the corresponding segment. When the absolute value of the slope and the correlation were beyond a threshold, the candidate segment was judged as a saccade segment. The same method was performed on blink detection. The main difference between the blink detection with the saccade detection is that the blink detection check the subsequence '010' and has a threshold of the maximal segment length.

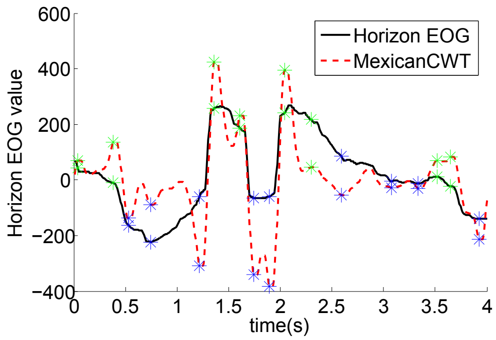

Fig. 4. The saccade detection segment

To reduce the complexity of extracting features from EOG, we detected the blink from extracted VEO and the saccade from extracted HEO. After blink, saccade and fixation (blink or saccade duration) being detected, we calculated the mean, maximum, variance, and derivative of the blink, saccade, and fixation. The features were extracted from a fixed 8 seconds non-overlap window. We eliminated the features if their correlation coefficients with PERCLOS were under a certain threshold. Table. I shows the finally chosen 36 features.

TABLE I

THE FEATURES EXTRACTED FROM EOG

Group	Features
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
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
fixation	mean/maximum of blink duration variance/saccade duration variance maximum/minimum/mean of blink duration/saccade duration

A simple but effective moving average filter was used to smooth the features, which could remove the components of small correlation with fatigue at the same time.

C. PERCLOS Calculating

We used the contour detection algorithm provided by OPENCV to detect the eye closure state (see [6] for detail). After the eye state being detected, we calculated the PERCLOS with a 60 seconds length window, and then smoothed the result with a 30 seconds moving average window. Each experiment contained 110 minutes PERCLOS data with the first 100 seconds and the tail segment being discarded, and the same method was also performed on the extracted EOG signals.

D. Data Partition

The EOG data is time dependent, and cannot be randomly divided. The time for different subjects to fall asleep is different, so the whole data cannot be split with a fixed interval. The training segment should include both sleepy and awake data. Therefore, we divided the EOG data into several continuous segments in this experiment. To get a long segment of fatigue period to predict, the EOG data was divided into five continuous segments with 22 minutes length. Among them, the four segments were used to train model, and the rest was used in prediction.

E. Regression Model

After EOG features being extracted, SVM with linear kernel and linear regression model were used to regress the features to PERCLOS data on each subject.

IV. RESULTS AND DISCUSSION

A. Forehead HEO and VEO Extraction

TABLE II

EXTRACTION RESULTS

Subject	HEO	VEO	Subject	HEO	VEO
1	0.9208	0.9159	8	0.9290	0.9508
2	0.8794	0.4380	9	0.9361	0.8772
3	0.8446	0.9432	10	0.8022	0.9464
4	0.9283	0.5640	11	0.7525	0.5787
5	0.8830	0.9394	12	0.6905	0.6983
6	0.8388	0.8221	13	0.8337	0.4948
7	0.8778	0.8509	14	0.8683	0.9196
Mean$\pm$std	0.8561$\pm$0.0707(HEO), 0.7814$\pm$0.1871(VEO)				

The traditional EOG contains HEO and VEO, so the extracting results contain both forehead HEO and VEO. The correlation coefficients between the forehead EOG and the traditional EOG on different subjects are illustrated in Table II. We also make comparison between two types of VEO: one is obtained by FASTICA and the other by the subtraction method. The results are shown in Fig. 5. The 'VEO-M' represents the forehead VEO obtained by subtraction method. The mean correlation coefficients of both HEO and VEO are 0.86 and 0.78, while VEO obtained by subtraction method is 0.66. The results show that the correlation coefficient obtained by FASTICA is higher than the subtraction method. Therefore, in this study, FASTICA is finally chosen to extract VEO.

Using the electrodes on forehead to record the EOG signals can reduce much discomfort to the subject, especially who wear sunglasses or eye-short glasses. A suitable electrode placement and the corresponding separating method need further research, which is useful for integrating the EOG electrodes into wearable devices.

B. Data Partition

Because different subjects may have different fatigue states during the driving simulation, the divided segment to predict is also somewhat different. In our experiment, the fatigue always happened between the second and fourth segments.

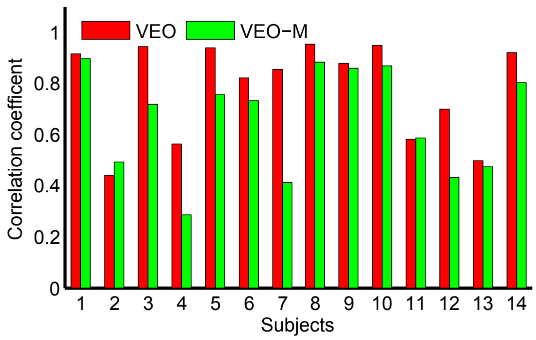

Fig. 5. The results of two methods to extract VEO

TABLE III
DATA SEGMENT PARTITION

#Predicting segment	#Subjects
2	2 3 4 5 7 10 11
3	1 13
4	6 8 9 12 14

Table III shows the number of the predicting segment for each subject. The rest four segments not shown in Table III are used to train the model. From the segment partition results, we can see that the prediction segments are mainly distributed in second and fourth segment.

C. Regression Prediction

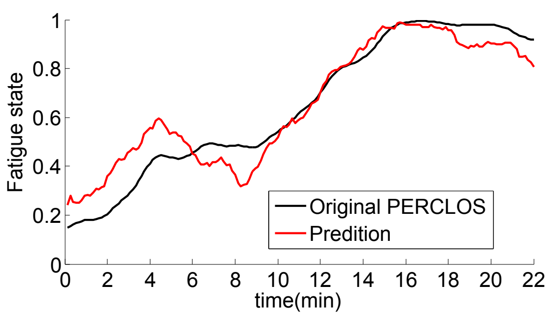

Fig. 6. Comparison between predicting fatigue curve and the original PERCLOS curve

Once the data were collected, the training segments were used to train the regression model and then the trained model was used to predict the test segment. Fig. 6 shows a subject's PERCLOS prediction with a segment of 22 minutes length, in which the red curve is the predicting results of the SVM and the black curve is the original PERCLOS curve.

The correlation coefficients of prediction results on all the 14 subjects are shown in Table IV. From Table. IV, we can see that the linear SVM gets a correlation coefficient of 0.88 on average, while the linear regression (LR) gets 0.74.

The PERCLOS is an easy accessible indicator to driving fatigue. With the assistance of eye tracking glasses we can get a more accurate PERCLOS data with less extra work. As eye tracking glasses is expensive, it can only be used to get the labels in training stage. After the model being trained well, the information extracted from forehead EOG signals is used to predict the fatigue state.

TABLE IV
PREDICTION RESULTS

Subject	SVM	LR	Subject	SVM	LR
1	0.9829	0.9799	8	0.9512	0.9442
2	0.7656	0.6335	9	0.8063	0.7882
3	0.9015	0.7785	10	0.8812	0.8500
4	0.9818	0.9898	11	0.8059	0.6335
5	0.8786	0.5740	12	0.9309	0.4215
6	0.9772	0.4215	13	0.8924	0.8550
7	0.9263	0.9349	14	0.6665	0.6233
Mean±std	0.8820±0.0921(SVM), 0.7448±0.1952(LR)				

V. CONCLUSION

In this study, we have introduced a novel electrode placement on forehead and proposed a corresponding algorithm to extract HEO and VEO from forehead EOG. The extraction results on 14 subjects show that the separating algorithm worked well on the proposed forehead electrode placement. The forehead is a promising placement to record EOG, which is more convenient for practical applications. The PERCLOS calculated from the videos recorded by eye tracking glasses provides a reliable index of driving fatigue. The regression model trained on forehead EOG achieves a fine prediction performance on each subject. The experiment is a meaningful trial for using forehead EOG to detect driving fatigue in future practical applications.

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