Detecting Slow Eye Movement for Recognizing Driver's Sleep Onset Period with EEG Features

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***Abstract*— Slow eye movement (SEM) is reported as a reliable indicator of sleep onset period (SOP) in sleep researches, but its characteristics and functions for detecting driving fatigue have not been fully studied. Through visual observations on ten subjects' experimental data, we found that SEMs tend to occur during eye closure events (ECEs). SEMs accompanied with alpha wave's attenuation during simulated driving was observed in our study. We used box plots to analyze the distribution of durations of different ECEs to measure sleepiness level. Experimental results indicate that the ECEs with SEM have higher duration distribution, representing higher sleepiness level, especially for those accompanied by alpha wave's attenuation. This verifies that SEM can be used as a reliable indicator for recognizing driver's SOP. In light of this and considering the possible accompanying of Electroencephalograph (EEG) wave changes, we propose a new algorithm for detecting SEM, which extracted EEG power related features from occipital O2 signal to add them into features set of horizontal Electro-Oculogram (HEOG) signal. Then, maximum relevance and minimum redundancy (mRMR) method was used for feature selection and support vector machine (SVM) was used to classify the SEM class and non-SEM class. Experimental results demonstrate that using EEG power related features can improve the algorithm's accuracy by an average 1.4%. The feature $P_{(\alpha+\theta)/\beta}$ was ranked highest by mRMR among all EEG features, indicating the interactive relationship between EEG waves and SEM.**

I. INTRODUCTION

Numerous drivers admit that they have fallen asleep at the wheel [1]. If the driver lapses into a sleep onset period (SOP) [2] without realizing it when performing some critical driving task is needed at the same time, the risk of crashing is significantly increased. For this issue, finding a reliable physiological signal indicator for driver's SOP is very meaningful. It is worth noting that slow eye movement is regarded as a reliable indicator for sleep onset period in a lot of sleep related studies. Slow rolling eye movements are mentioned appearing in the transition from wakefulness to sleep in many sleep scoring manuals [2]. Rechtschaffen and Kales linked the emergence of SEM to the disappearing of EEG alpha wave as one indicator of sleep stage 1 [3]. With eyes closed, SEMs showed negative correlation with EEG power in 1-14 Hz frequency range [4], which included alpha wave frequency range of 8-12 Hz.

However, SEM has received little attention in the field of driving fatigue detection. In our experiments, we found SEM almost always occurred in ECEs. Moreover, SEM was observed to be accompanied by alpha wave's attenuation on O2 channel during our simulated driving experiments. This accompanying of alpha's attenuation can further verify SEM as a reliable indicator for SOP, since alpha's attenuation is determined to be most valid marker of sleep onset [2], [5]. But the ECEs with SEM seemed to appear before the ECEs with alpha's attenuation in our study. Therefore, detecting SEM is very useful for driving fatigue detection. Almost existing algorithms for automatic detecting SEM were developed in sleep related researches, which used wavelet energy features or statistical features [6], [7]. Under simulated driving condition, we proposed approach using features based on wavelet singularity and combining the SVM classifier in our previous work [8]. In general, all these existing methods were based on the analysis of HEOG signal without using any EEG information. Considering possible accompanying of EEG wave changes except for alpha wave change, we propose a new SEM detection algorithm with EEG power related features in this paper. Moreover, the feature selection method (mRMR) were used to further analyze the vital function of EEG power related features.

II. MATERIALS

A. Experiment Procedure

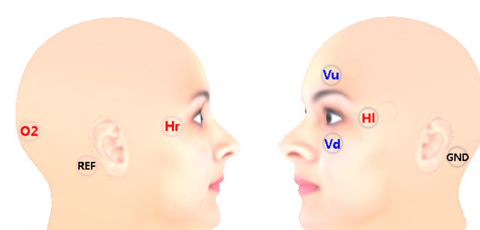

Fig. 1. The placements of all electrodes used in our experiment. Here, horizontal EOG: HEOG=Hr-Hl and vertical EOG: VEOG=Vu-Vd.

Ten normal students (7 male and 3 female, aged 23 $\pm$ 3.4) who had regular siesta habits were recruited from Shanghai Jiao Tong University. The starting time of each experiment was half an hour before their regular sleep time at noon about at 12:20 and each experiment lasted for more than 2 hours. In our virtual-reality-based simulated driving environments, the subject were seated in a real vehicle (without the unnecessary

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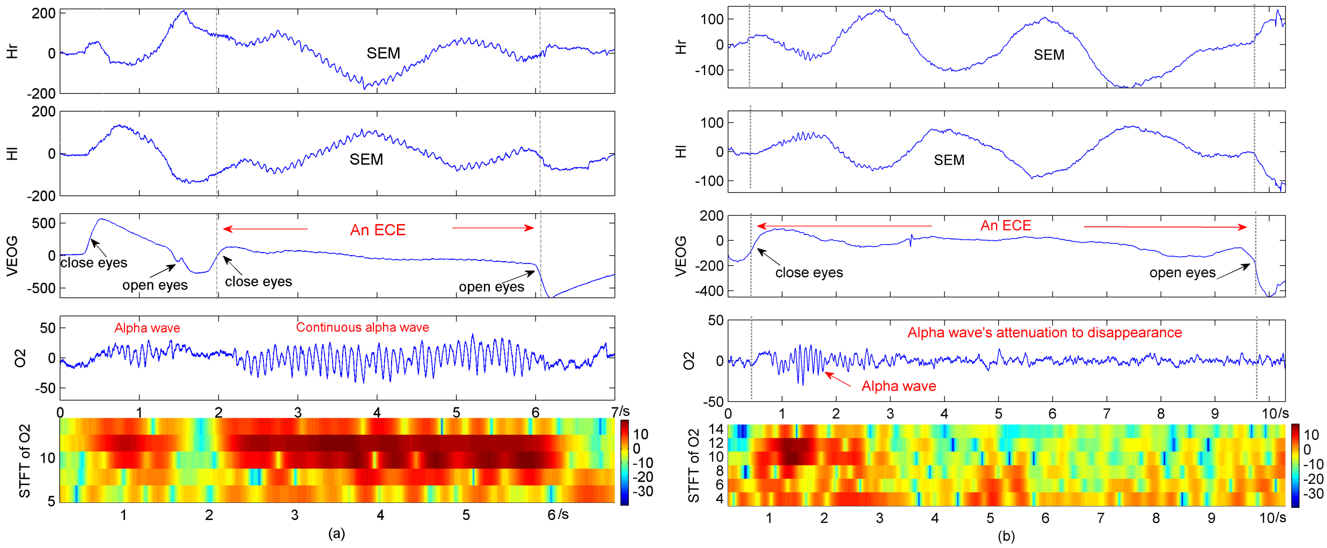

Fig. 2. (a) The SEMs with continuous alpha wave in an ECE (about 2-6 s). (b) The SEMs with alpha wave's attenuation to disappearance in an ECE (about 0.5-9.5 s). SEM appears on two HEOG channels (Hr and Hl, near the outer canthi of eyes), having binocular synchrony with opposed-phase deflections. An ECE can be determined as the period between the upward trend line caused by closing eyes and the downward trend line caused by reopening eyes on VEOH signal (VEOG = Vu-Vd). The Short-Time Fourier Transform (STFT) of O2 shows alpha (8-13 Hz) power change over time.

engine and other components) and drove a virtual car in a virtual four-lane highway scene shown on a big LCD screen in front of the real vehicle by operating the real vehicle's steering wheel and gas pedal. The virtual highway was mostly straight and monotonous to induce subject fatigue more easily. During driving, closing eyes deliberately but without feeling drowsy was strictly prohibited. However, this did not prevent the occurrences of a large number of ECEs. Subjects were asked to complete the Epworth Sleepiness Scale (ESS). Their ESS values were 9.8 ± 1.5.

B. Data and Video Recording

The placements of all electrodes used were shown in Fig. 1. The data from two HEOG electrodes (Hr, Hl), two VEOG electrodes (Vu, Vd), and one EEG electrode (O2) were recorded at a 1000 Hz sampling rate using the ESI NeuroScan System. A camera was set to monitor the subject's face to clearly recognize open or closed eye states. Both images from the camera and real-time displaying HEOG/EEG signals in NeuroScan software interface were displayed on the same computer screen synchronously. The computer screen image change over time was recorded into a video file for subsequent reviewing and analysis.

III. Methods

A. Visual Observation and Statistical Analysis

Any data epoch which meets the following commonly used visual criteria [7] is scored as SEM epoch; otherwise, non-SEM epoch. The criteria are: (1) the slow sinusoidal excursion (0.2-0.6 Hz) lasting more than 1 second; (2) amplitude between 20 and 200 μV; (3) binocular synchrony with opposed-phase deflections in the two channels (Hl, Hr); (4) onsets of SEMs in the right channel (Hr) and in the left channel (Hl) occur within 300ms of one another; (5) absence of artifacts in HEOG (Hl-Hr). An eye closure event (ECE) was determined according to the VEOG signal changes (Fig. 2 (a)) and recorded videos showing the correspondence between eye movements and VEOG signals. We found in ECEs SEMs were often with continuous alpha wave, and sometimes with alpha's attenuation on O2 channel. To our best knowledge, the SEM accompanied by alpha's attenuation was first observed in our simulated driving experiments. Through careful observation, we found that there are three main kinds of ECEs alternately appearing in driving process: the ECEs without SEM; the ECEs with SEM and accompanied by continuous alpha (Fig. 2 (a)); and the ECEs with SEM and accompanied by alpha's attenuation to disappearance process (Fig. 2 (b)). We used box plots to analyze their duration distributions to describe sleepiness level.

B. The Algorithm for Detecting SEM

The problem of detecting SEM was transformed to classifying SEM class and non-SEM class. For any SEM epoch or non-SEM epoch, it was divided into 3-s length data fragments with a sliding step of 0.5 s and each data fragment was labeled as SEM class or non-SEM class, respectively. For any data fragment, we extracted features from both HEOG (Hr-Hl) signal and O2 signal (Fig. 2) to form training features sample sets for two classes. Then, we used mRMR to select features and SVM to classify the two classes.

C. EEG Power Related Features from O2 Signal

Driving fatigue detection based on EEG usually investigated three frequency bands and two factors of their combination: *theta* (θ, 4-8 Hz), *alpha* (α, 8-13 Hz), *beta* (β, 13-20 Hz), *(theta+alpha)/beta* and *beta/alpha* [9]. In this study, we found SEMs were often accompanied by alpha wave change. Moreover, the existing studies reported that SEMs correlated negatively with EEG power in 1-14 Hz frequency range and correlated positively with the 15-30 Hz frequency range with eyes closed in sleep process [4]. Therefore, considering above information, we extracted some EEG power related features. Each 3-s data fragment from O2 signal was subjected to fast Fourier transform (FFT). Then we calculated power spectral density (PSD) of each of three basic EEG wave frequency bands respectively as EEG features P_θ, P_α, P_β and other two EEG combination factor features $P_{(\alpha+\theta)/\beta}$ and $P_{(\beta/\alpha)}$ were also calculated.

D. Features from HEOG signal

We extracted 25 features from HEOG signal, which was done in parallel with feature extraction from O2 signal.

1) Features based on wavelet energy: In this study, we extracted wavelet energy features in the same way as our previous work [8]. Before using wavelet transform, HEOG signal was filtered below 40 Hz and had a re-sample frequency of 500 Hz. Then, Daubechies order 4 wavelet with orthogonal basis was chosen to decompose a 3-s data fragment of HEOG signal into the 10th level. Based on the obtained wavelet coefficients, we got 7 wavelet energy features by calculating wavelet energy for each resolution level's detail signal from D10 (0.35-0.70 Hz) to D5 (22.32-44.64 Hz), and calculating wavelet energy for one approximation signal A10 (0-0.35 Hz) of the 10th level.

2) Features based on wavelet singularity analysis: Saccades appeared a lot during simulated driving under the condition of wakefulness with eyes open. The signal waveform caused by saccade was like rectangular wave with many instantaneous change points on HEOG signal. But when SEM occurred, the caused signal waveform was like smooth and slow sinusoidal wave (Fig. 2). If Mexican hat mother wavelet with even symmetry structure, was used to do the convolution with the instantaneous change point with local even symmetry, the convolution results will be local even symmetry; otherwise, the result will be local odd symmetry [8]. For distinguishing different characteristics between saccades and SEM, the Continuous Wavelet Transform (CWT) using Mexican hat mother wavelet was applied into each 3-s HEOG signal and thus got CWT-HEOG signal. Then, the following seven statistical features were extracted: the mean, standard deviation, entropy, skewness and kurtosis values of CWT-HEOG signal; the maximum value and the second largest value of the absolute value of CWT-HEOG signal.

3) Features based on statistics: For each 3-s data fragment of HEOG signal, the following 11 statistical features were extracted: the mean, standard deviation, skewness, kurtosis and entropy of the signal amplitude; the mean, standard deviation, skewness, kurtosis and entropy of the signal difference; the absolute value of the difference between the maximum and the minimum of the signal amplitude.

E. Feature Selection and Classification

The mRMR feature selection method is adopted to sequentially select features with the maximal relevancy and minimal redundancy based on mutual information theory [10]. The ranking value of a feature in feature sequence corresponds to this feature's ability to distinguish two classes. For classification, we used the SVM with RBF kernel function. By grid search for two parameters, C ([0, 1024]) and γ ([0.1, 2]), the best result was obtained.

IV. Results and Discussion

A. Characteristics of SEM

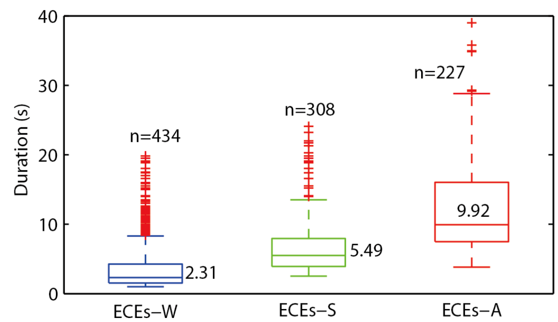

Fig. 3. The duration distributions of three kinds of ECEs by box plots.

Fig. 3 gives the duration distributions of three kinds of ECEs, which alternately appeared during simulated driving. The ECEs-W including all ECEs (more than 1 s) without SEM, has the lowest duration distribution with the median value 2.31 s. In contrast, the ECEs-A including all ECEs with SEM and alpha's attenuation, has the highest duration distribution with the median value 9.92 s. The ECEs-S including all ECEs with SEM and continuous alpha wave, has the moderate duration distribution. The duration distribution is used to represent sleepiness level. The ECEs with SEM (ECEs-S and ECEs-A) show higher sleepiness level, especially for those with alpha wave's attenuation (ECEs-A). We all know that alpha's attenuation to disappearance belongs to sleep stage 1 [2]. Therefore, the alpha's attenuation on O2 channel accompanying SEM on HEOG further verifies SEM as a reliable indicator for sleep onset period during simulated driving.

B. Classification Performance

For physiological signals, individual variations usually exceed the expected range of EEG alpha's frequency range and amplitude. Therefore, the SEM detection algorithm was done within each individual. In addition, because SEMs tend to occur in ECEs, but the number of each of the three kinds of ECEs was not fixed for each subject due to the complicated and repetitive driving fatigue state transform. The ratio between the time length of all SEM epochs and that of non-SEM epochs varied about from 1:90 to 1:23 among ten subjects. Therefore, the number of feature samples from SEM class was usually less than that from non-SEM class. To deal with this imbalanced two-class classification problem, we used simple under-sampling strategy. For individual data section, the proportion of training set and testing set is 7:3. During training, we randomly selected feature samples from non-SEM class with equal number to the size of SEM class

TABLE I

THE COMPARISON OF THE MEAN ACCURACY VALUES BETWEEN THE HEOG FEATURE GROUP AND THE HEOG+O2 FEATURE GROUP OVER TEN SUBJECTS

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	Mean ± SD
HEOG	92.4	93.8	91.8	91.2	91.1	90.5	92.9	90.7	92.2	92.9	92.0 ± 1.1
HEOG+O2	94.1	95.9	94.2	92.3	91.9	92.0	94.2	91.8	94.1	93.7	93.4 ± 1.4

to form a balanced training set. Then, we also got a balanced testing set in the same way. This process was repeated 20 times, so we got 20 groups of balanced training and testing sets.

To investigate the effect of adding EEG power related features on classification accuracy, the detection algorithm was done respectively for two feature groups: 1) HEOG feature group including the features extracted from HEOG signal; 2) HEOG+O2 feature group including the features extracted from both HEOG and O2 signals. For each feature group, mRMR ranked the features of two classes in original imbalanced training set and a feature sequence was obtained. Then, For each of 20 groups of training and testing sets, SVM was used to train the balanced training set and the best classification accuracy was got by forward searching for the feature sequence. Considering the selected features and trained model, testing was done in the corresponding testing set. Table. I gives accuracies of two feature groups over ten subjects. These comparative results demonstrate that the mean accuracy values for the HEOG+O2 feature group are higher than those for the HEOG feature group, due to the adding of EEG power related features.

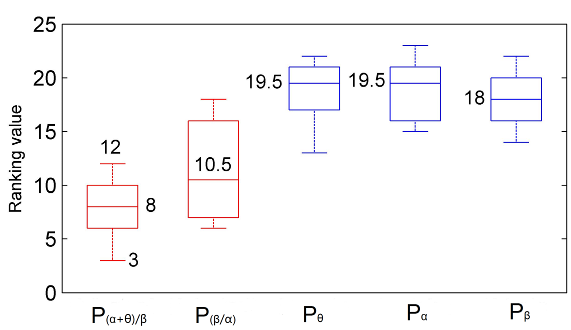

Fig. 4. The ranking values of EEG power related features by mRMR among all features (HEOG+O2).

To show the importance of these EEG power related features among all features, Fig. 4 gives the distribution of ten ranking values of each EEG power related feature. Each ranking value was obtained by mRMR ranking each subjects' original training set for HEOG+O2 feature group. The ranking value corresponded to the feature importance, which indicated this feature's ability to discriminate between SEM and non-SEM classes. The most useful features were those found with the highest ranking value (close to 1) distribution. From Fig. 4, the feature $P_{(\alpha+\theta)/\beta}$ is found to be most useful, with median ranking value 8, the highest ranking value 3 and the lowest ranking value 12. Followed by the feature $P_{(\beta/\alpha)}$ with median ranking value 10. Other features have median ranking values near 18. We found the number of selected features during different training process with forward searching for feature sequence was at least 15, thus the feature $P_{(\alpha+\theta)/\beta}$ played an important role in classification. This result is consistent with the conclusion that SEM correlated negatively with 1-14 Hz frequency range (α, θ within this range) and positively with 15-30 Hz (β within this range) in sleep process [4]. Besides, $(\alpha+\theta)/\beta$ and β/α reported as two reliable factors for detecting fatigue [9], are also proved to be important features for detecting SEMs.

V. CONCLUSION

The SEM is observed to be accompanied by alpha wave's attenuation in this study and it can be regarded as a reliable indicator for driver's SOP. The experimental results demostrate that adding EEG feature group to HEOG feature group improves the accuracy of algorithm for detecting SEMs. The importance of the EEG feature $P_{(\alpha+\theta)/\beta}$ seems to indicate the interactions between EEG waves and SEM during SOP in the simulated driving process.

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