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

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Introduction

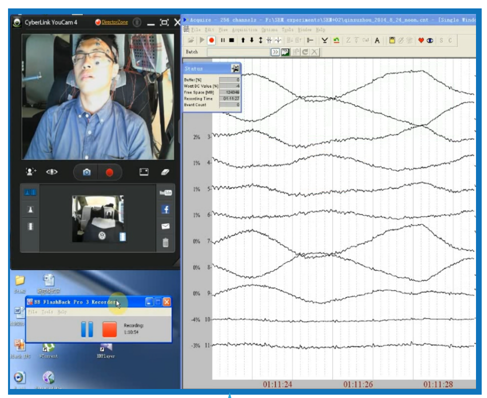
Numerous drivers admit that they have fallen asleep at the wheel. In a lot of sleep related studies, slow eye movement (SEM) is regarded as a reliable indicator for sleep onset period (SOP) and has a negative correlation with EEG power in 1-14 Hz frequency range. However, SEM has received little attention in the field of driving fatigue detection. In our simulated driving experiments, SEMs were found to almost occur in eye closure events (ECEs) and SEMs' occurrence was often accompanied by EEG alpha wave's attenuation. Since alpha wave's attenuation is determined to be most valid marker of sleep onset, SEM can be further verified as a reliable indicator for SOP. Therefore, detecting SEM is very useful for identifying driver's SOP. We proposed a new SEM detection algorithm with newly-added EEG power related features and the feature selection method (mRMR) was used to further analyze the vital function of these EEG features.

Materials

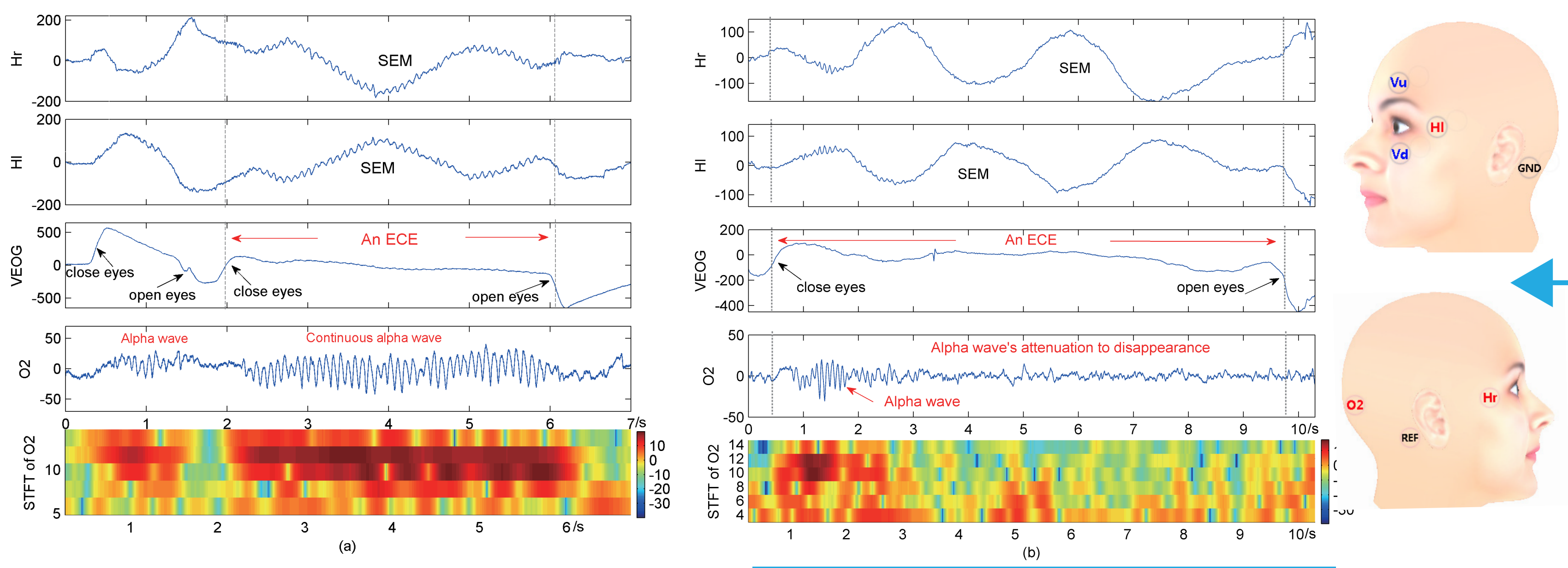
Virtual-reality-based simulated driving environment

A camera was set to monitor the subject's face

Each experiment started at 12:00 and lasted for about 2 h. Ten subjects had regular siesta habits and their Epworth Sleepiness Scale (ESS) values are 9.8 ± 1.5. Both images from the camera and real-time displaying of HEOG/EEG signals were recorded into a video file for subsequent manual tagging



Manual tagging for SEM epoch

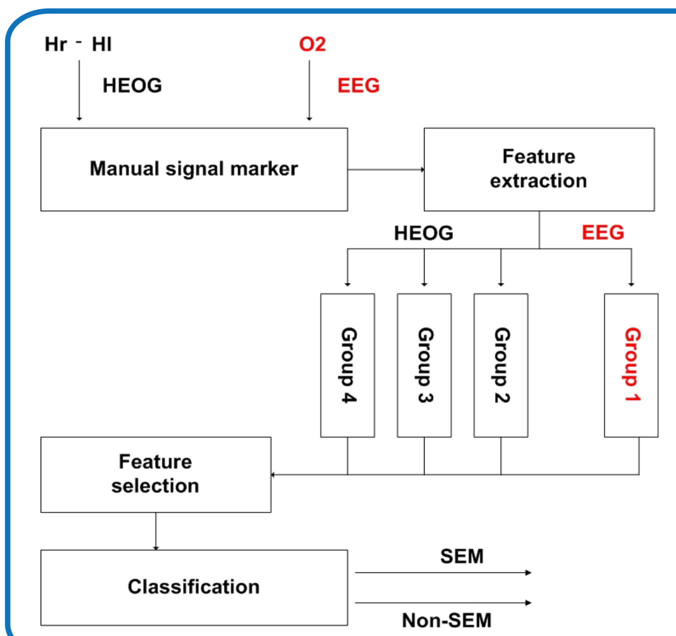


The SEMs with continuous alpha wave

The SEMs with alpha wave's attenuation

SEM is slow sinusoidal excursion (0.2-0.6 Hz), appearing on both two HEOG (Hr-Hl) channels (Hr and Hl, near the outer canthi of eyes) and 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 VEOG signal (VEOG=Vu-Vd). The short-time Fourier transform (STFT) of O2 shows alpha power change over time.

The Algorithm for Detecting SEM



Mannual signal marker: For each subject, any data epoch meets the visual criteria for SEM was marked as SEM epoch; otherwise, non-SEM epoch. Any SEM epoch or non-SEM epoch was divided into 3-s data fragments with a sliding step of 0.5 s and each data fragment was labeled as SEM classs or non-SEM class.

Feature extraction: For any 3-s data fragment, we extracted 4 groups of features from HEOG and O2 signals:

* Group 1: EEG power related features from O2. We calculated power spectral density (PSD) for each of three basic EEG wave frequenc bands $P\theta$ (theta(θ, 4-8Hz), $P\alpha$ (alpha(α, 8-13 Hz)), $P\beta$ (beta(β, 13-20 Hz)) and other two PSD factors $P(\theta+\alpha)/\beta$ ((heta+alpha)/beta) and $P(\beta/\alpha)$ (beta/alpha) as EEG power related features.

* Group 2: 7 Wavelet energy features.

* Group 3: 7 Wavelet singularity features.

* Group 4:11 statistic features.

Feature selection and Classification: The mRMR feature seletion method is adopted to sequentially select features with the maximal relevancy and minimal redundancy based on mutual information theory. For classification, we used the SVM with RBF kernel function.

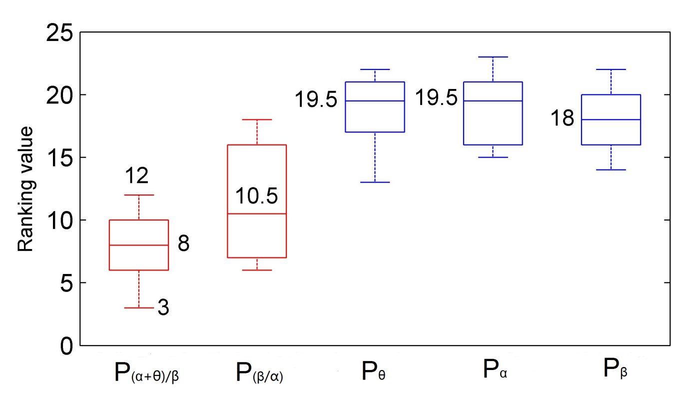
Results and Discussion

Classification results by SVM

	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

The SEM detection algorithm was done within each of ten subjects. The detection algorithm was done respectively for two groups of features: HEOG featue group and HEOG+O2 feature group which include the features from both HEOG and O2 signals. For each group feature, mRMR ranked the features of two classes in training set and SVM was used to train the features set. The best classification accuracy was got by forward searching for the feature sequence.

The table gives classification accuracy values respectively for two groups of features over ten subjects. Experimental results demostrate that the adding of EEG power related features can improve the algorithm's accuracy by an average 1.4%.



The figure 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 correspond to the feature importance, which indicated this feature's ability to discriminate between SEM and non-SEM classes. The feature $P(\theta+\alpha)/\beta$ is found to be most useful and this seems to indicate the ineractions between EEG and SEMs during sleep onset in the simulated driving.

(1) ECEs-W: the ECEs *without* SEM.

(2) ECEs-S: the ECEs *with* SEM and continuous alpha wave.

(3) ECEs-A: the ECEs *with* SEM and alpha wave's attenuation.

The right figure gives the duration distributions of the three kinds of ECEs mentioned above. The duration distribution represents 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). The numerous ECEs with both SEM and alpha wave's attenuation (ECEs-A) further verifies SEM as a reliable indicaor for sleep onset period (SOP) during simulated driving.