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Electroencephalogram and electrocardiograph assessment of mental fatigue in a driving simulator

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ABSTRACT

Mental fatigue is a contributing factor to some serious transportation crashes. In this study, we measured mental fatigue in drivers using electroencephalogram (EEG) and electrocardiograph (ECG). Together, thirteen healthy subjects performed a continuous simulated driving task for 90 min with simultaneous ECG and multi-channel EEG recording of each subject. Several important physiological parameters were investigated using preprocessed ECG and EEG signals. The results show that the EEG alpha and beta, the relative power, the amplitude of P300 wave of event-related potential (ERP), the approximated entropy of the ECG, and the lower and upper bands of power of heart rate variability (HRV) are significantly different before and after finishing the driving task ($p < 0.05$). These metrics are possible indices for measuring simulated driving mental fatigue.

1. Introduction

Mental fatigue refers to changes in the psycho-physiological state that people experience during and following the course of prolonged periods of demanding cognitive activity that require sustained mental efficiency (Kato et al., 2009). In other words, mental fatigue is limited solely to a mental state arising from a behavioral situation that includes a long-term continuous, repetitive performance of some mental task. Hulst et al. (2001) thought driving was an example of a complex task that required continuous attention in order to detect possible hazard, and the main time-on-task effect in driving was a progressive withdrawal of attention from road and traffic demands. The deteriorating driver performance associated with driving mental fatigue presents a serious safety risk. According to a report by the Parliament of the Commonwealth of Australia, driving mental fatigue is believed to account for 20–30% of all traffic accidents (The Parliament of the Commonwealth of Australia, 2000). Experts agreed that the actual contribution of a driver's mental fatigue to road accidents might be much higher. Developing and establishing an accurate and non-invasive real-time system for monitoring a driver's mental fatigue are important to reduce road accidents and lower the number of injuries in traffic safety.

Driving simulator studies have dominated the research on driving mental fatigue mainly due to the safe, low cost, well-controlled conditions and ease of data collection (Reed and Green, 1999). In addition, driving simulation allows the evaluation of a wider range of driving situations, especially those that are dangerous or physically threatening. Such situations, which for obvious reasons cannot be tested on the road or even on a test track, include assessing the ability of the subject to avoid collisions, as well as determining the effects of alcohol, drugs and fatigue on driving (Lew et al., 2005). Philip et al. (2005) concluded that fatigue could be equally studied in real and simulated driving environments. Shechtman et al. (2009) found that the same trends existed between driving errors made on the road and in the simulator, thus validating the simulator. Young et al. (2009) validated the Enhanced Static Load Test (ESLT) as predictive of visual event reaction times during open-road driving for the range of experimental conditions and tasks considered.

Previous studies have aimed to find the sensitive indices for evaluating driving mental fatigue based on performance and perceptual, electrophysiological, psychological and biochemical measurements. A number of methods have been proposed to detect mental fatigue. Reimer et al. (2006) tried to establish the validity of driving behavior measures collected during a simulation scenario using self-reported survey indicators of driving behavior. They considered these measures as valid indicators of the behaviors of interest. Lal and Craig (2002) and Lal et al. (2003) used a video image of the driver's face as an independent variable for driver

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fatigue when they developed an algorithm for detecting different levels of driver fatigue based on EEG and psychological assessment. They concluded that these image-based signs of fatigue had excellent reliability for recognizing driver fatigue. However, self-report techniques cannot track the dynamically changing state of fatigue without confounding or compromising task performance. The parameters of the image may vary in different environmental situations and driving conditions, and thus devising different detection logics may be required for different types of vehicles. A recent tendency in ergonomic research is to choose physiological and psychological measures to assess the driving mental fatigue state. Several EEG studies have been related to driving mental fatigue. Some of them reported that EEG spectral parameters would change when mental fatigue occurred. For example, the proportion of low frequency EEG waves such as theta and alpha rhythms may increase, while higher frequency waves such as beta rhythms may decrease (Lal and Craig, 2002). Schmidt et al. (2009) found that the amplitude of the stimulus-induced P3 event-related potential (ERP; for a review see Polich, 2007) decreased linearly with time during a simulated driving task. Heart rate and heart rate variability (HRV) have also been used as physiological measures of workload during driving conditions. Apparies et al. (1998) considered cardiovascular measures such as heart rate and HRV might serve as early indicators of fatigue. Li et al. (2004) applied power spectra analysis of HRV to assess drivers' mental fatigue during simulated driving tasks. Some researchers reported heart rate changes during certain driving tasks (Hartley et al., 1994; Liu et al., 2004). The rapid development of high resolution brain imaging machines and imaging techniques, such as Functional Magnetic Resonance Imaging (fMRI) and Magnetoencephalography (MEG), made it especially possible to study the neural pathways and brain dynamics involved in the simultaneous performance of multiple tasks, such as modulating reaction times to visual events while viewing a driving video, with and without conversation (Bowyer et al., 2009; Hsieh et al., 2009).

Driving mental fatigue is a complex phenomenon involving physical psychosocial and behavioral processes, and no single-parameter measures could be sufficiently sensitive and reliable enough to quantify driving mental fatigue. In this paper, multiple measures are combined to assess driving mental fatigue. The subjective self-reporting measures and the reaction time (RT) to visual Oddball task stimuli were used to verify that long-term driving tasks would induce mental fatigue in the subjects. Next, the P300 amplitude and latency based on visual Oddball task stimuli, the power spectral parameters of HRV, Approximate Entropy (ApEn) of ECG and the power spectral parameters in four frequency bands (delta, theta, alpha, beta) of EEG were applied to estimate driving mental fatigue under the simulated condition. The multi-parameters analysis may provide a novel approach for measuring simulated driving mental fatigue.

2. Methods

2.1. Subjects

To reduce inter-subject differences, thirteen male volunteers (mean age: 25.8 years; range: 22–27 years) were recruited from students of Xi'an JiaoTong University and were randomly assigned to perform the experiments. Each subject was requested to sign a consent form to indicate that the participation was voluntary. The experiments were approved by the institutional ethics committee. All the subjects lacked actual driving experience, and none of them were able to operate a stick shift car. To complete the oddball task, the subjects were familiar with operating a computer and had experience playing video games. The subjects were trained prior to the experiment until they performed the driving simulator exercise skillfully (if a subject could perform the driving simulator for 15 min without any errors, then the training was complete. The training time ranged from 3 h to 6 h across all subjects). When a subject is able to perform the simulator skillfully, he is regarded as a driver with some driving experience. Based on the principle put forward by Lal et al. (2003), a lifestyle questionnaire was administered. The participants were only admitted into the study on the condition that they were currently healthy, did not work night shifts, and did not use prescription medication or have medical contraindications such as severe concomitant disease, alcoholism, drug abuse, and psychological or intellectual problems likely to limit compliance (as determined by a pre-study interview). All of the subjects also had normal or corrected-to-normal vision and were right-hand dominant.

2.2. Apparatus and data acquisition

The Neuroscan system (Synamps^2, Scan 4.3, El Paso, TX, USA) was used to record the physiological data. EEG was recorded using a thirty-two channel electrode cap with sintered Ag/AgCl electrodes following the international 10–20 Montage system (Jasper, 1958). One channel of the ECG and both the vertical and horizontal channels of electrooculogram (EOG), were recorded simultaneously. The unipolar reference region was linked at the right and left earlobes, and the ground electrode was located at AFz (A-Ear lobe, F-Frontal lobe, z-zero, refers to an electrode placed on the mid-line). The connecting impedance was kept below 5 kΩ for EEG electrodes and 10 kΩ for EOG and ECG electrodes. All physiological signals were sampled at 500 Hz with a 0.05–70 Hz band-pass filter and 50 Hz notched.

Driving simulators (WM-5 V, China), which consist of a car frame with a built-in steering wheel, gas and brake pedals, clutch, manual shift and a horn and turn signal, etc., are widely used as teaching equipment for the driving school students in China. As teaching equipment for driving, the performance method in the simulator is the same as in a real car, but the driving environment is simpler in the simulator than in the real world. The visual display of the virtual reality (VR)-based driving simulation environment was a 19-inch Liquid Crystal Display (LCD) positioned at a distance about 80 cm from the subject's eyes. The LCD showed the road environment and the current speed. The system also produced simulated engine noise and nearby traffic noise. The simulated route and traffic signs were standardized according to national traffic law.

The recorded data were visually inspected and data segments containing possible residual artifacts were eliminated. EEG larger than +100 uV were rejected as artifact. EOG artifact was also removed by using EOG signals as predictors of the artifact voltages at each EEG electrode. The ERP was averaged using the epoch data of 200 ms pre-stimulus and 800 ms post-stimulus. ECG raw data were preprocessed using wavelet-denoising (Quian Quiroga and Garcia, 2003).

2.3. Experimental design

Previous literature pointed out that driving mental fatigue could occur in a monotonous driving environment (Thiffault and Bergenron, 2003). A situation is said to be monotonous when the stimuli remain unchanged or change in a predictable manner, resulting in sensory stimulation that is constant or highly repetitive (McBain, 1970). Thus, a highway scene was selected for this experiment. Furthermore, the simulated driving task was designed with the following requirements: the route was simple so that the drivers could complete the task as easily as possible, there were few scenery changes and moving objects in the three-lane road, there was no inclination on driving route to reduce outside stimuli, and a very light curvature was chosen so that drivers should pay attention

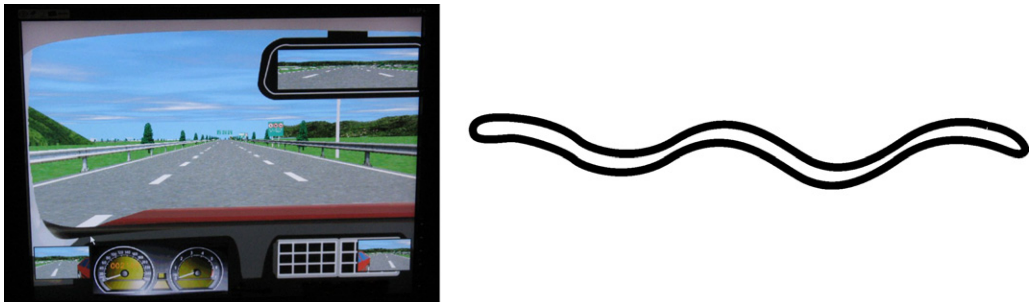

Fig. 1. The simulated scene and route.

to their steering at all times (Fig. 1). One lap would take approximately 7 min if the subjects kept the car speed at approximately 100 km/h. The participants were allowed to drive the simulator at any speed they chose. Each driving experiment lasted approximately 90 min.

In the pre-experiment, mental fatigue was induced in both male and female subjects after a simulated driving task, and the indices of EEG and ECG tended to change similarly between the genders. However, the three female subjects were barely able to sustain the driving task more than 90 min due to exhaustion (the longest sustained driving task time for females was 82 min). Hence, only male subjects were selected to take part in this experiment.

To assess the sustained attention level of drivers, subjects were requested to perform an Oddball task (Gentask, Neuroscan Stim2, El Paso, TX, USA) at the beginning and end of the driving task. In the Oddball task, the subjects should respond to target stimuli that occur infrequently and irregularly within a series of standard stimuli (Huettel and McCarthy, 2004). The Oddball paradigm consisted of a red and a green circular image randomly displayed on the screen. The probability of appearance was 0.85 for the red circular image and 0.15 for the green circular image. The duration of stimuli was 160 ms, and the inter-stimulus interval varied randomly between 1000 and 1200 ms. The Oddball task included 300 stimuli and lasted for approximately 5.5 min. Subjects were instructed to respond to the green images (infrequent stimuli) as quickly as possible using the mouse.

2.4. Experimental procedure

This study was conducted in a dimly lit, sound-attenuated and temperature-controlled laboratory after training the subjects. The entire experiment lasted approximately 120 min, including two Oddball tasks and a simulated driving task. Participants were requested to sleep adequately the day before the test and to refrain from consuming alcohol, caffeine, tea or food, as well as smoking, approximately 12 h before the test. Informed consent was obtained from all subjects prior to the study.

Inter-individual variation in the phase of circadian rhythms has been attributed to factors such as age, gender and especially morningness–eveningness, which is reflected in the individual's preference for sleep–wake timing (Vink et al., 2001). The experiment was conducted at 9:00–11:00 AM or 3:00–5:00 PM because this is the time for the subjects' normal daily work. Before the experiment, the subjects were informed of the entire experimental procedure and were given instructions. Next, the first Oddball test was started after the subjects reported their mental fatigue feelings. Then, the subjects performed the simulated driving task for 90 min without any break. During the driving, all subjects should restrict unnecessary movements as much as possible and try their best to keep car within a range of speeds and avoid a car accident. To maintain a monotonous driving environment, there were no questionnaires, nor any additional measurements during the driving. After the driving task, another Oddball task (with different stimuli sequences as described above) was performed. At the end of each experiment session, the subject's self-reports were investigated again.

2.5. Data analysis

To investigate the effects of time-on-task, the measurements were carried out at two timepoints: the beginning and the end of the driving task. All data were coded and analyzed using SPSS (SPSS 13.0 for Windows, September 1, 2004) for paired *t*-test for the small sample number in this study (the single sample K–S check in SPSS indicated all data are normally distributed, and *p* was well below 0.05).

3. Results

3.1. Self-report

The subjects in the experiment reported that they felt tired, bored and drowsy when the driving task was over. They were yawning occasionally during the driving task and reported difficulties in concentrating their attention on the driving task. Eleven of the subjects thought that the above-mentioned feeling might appear approximately after only 30 min of driving and strengthened with increasing driving time. However, according to Li's score (Li et al., 2004), the mental fatigue scores increased from 1.31 to 5.46 ($p < 0.005$) at the end of the task. Therefore, all of these physiological symptoms indicated that driving mental fatigue was induced by 90 min driving task.

3.2. Reaction time and error rate of the Oddball task

The errors for the Oddball tests were defined as either no response to the target stimuli or responses to non-target stimuli (for example, if a subject missed the green stimuli or responded to the red stimuli). Most errors resulted from responding to non-target (red) stimuli, and only a few errors were produced by missing target (green) stimuli. The percentage of errors calculated in the experiment included both types of errors.

The reaction time (RT) increased from 356.35 ms (Std deviation = 29.80; Std error mean = 8.26) to 376.65 ms (Std deviation = 39.40; Std error mean = 10.93) during the driving task. The paired *t*-test showed a significant difference in RT between the beginning and the end of the driving ($t = -3.946$, df = 12, $p = 0.002$), but the percentage of errors did not show a statistical difference; however, the percentage of errors did increase slightly after the driving task ($t = -0.09$, df = 12, n.s.).

Table 1
Mean (Std deviation; Std error mean) values of relative power from EEG spectra analysis during the beginning and the end of the driving task for the delta, theta, alpha and beta rhythms.

Rhythm	Region the beginning the end value of t, p
Delta	1 0.440(0.106; 0.029) 0.390(0.131; 0.036) $t = 1.76$, $p = 0.104$
	2 0.496(0.104; 0.029) 0.474(0.096; 0.027) $t = 1.81$, $p = 0.092$
	3 0.503(0.129; 0.036) 0.489(0.092; 0.025) $t = 0.76$, $p = 0.465$
	4 0.411(0.227; 0.063) 0.324(0.141; 0.039) $t = 2.22$, $p = 0.056$
	5 0.435(0.128; 0.035) 0.421(0.125; 0.035) $t = 0.60$, $p = 0.561$
Theta	1 0.225(0.091; 0.025) 0.317(0.167; 0.046)* $t = -2.53$, $p = 0.026$
	2 0.184(0.045; 0.012) 0.212(0.054; 0.015)* $t = -2.24$, $p = 0.045$
	3 0.160(0.038; 0.011) 0.176(0.044; 0.012) $t = -1.91$, $p = 0.080$
	4 0.117(0.037; 0.010) 0.140(0.041; 0.014)* $t = -2.35$, $p = 0.035$
	5 0.135(0.046; 0.013) 0.162(0.049; 0.014) $t = -1.86$, $p = 0.088$
Alpha	1 0.136(0.047; 0.013) 0.145(0.053; 0.015) $t = -0.75$, $p = 0.466$
	2 0.154(0.053; 0.015) 0.183(0.069; 0.019)* $t = -2.93$, $p = 0.013$
	3 0.169(0.061; 0.017) 0.193(0.064; 0.018)* $t = -2.85$, $p = 0.015$
	4 0.177(0.069; 0.019) 0.219(0.062; 0.017)** $t = -3.50$, $p = 0.004$
	5 0.153(0.047; 0.013) 0.215(0.110; 0.030)* $t = -2.94$, $p = 0.012$
Beta	1 0.199(0.075; 0.021) 0.149(0.062; 0.017)* $t = 2.24$, $p = 0.045$
	2 0.166(0.086; 0.024) 0.131(0.060; 0.017)* $t = 2.32$, $p = 0.039$
	3 0.169(0.108; 0.030) 0.142(0.075; 0.021) $t = 1.70$, $p = 0.115$
	4 0.296(0.173; 0.048) 0.318(0.140; 0.039) $t = -0.74$, $p = 0.475$
	5 0.277(0.115; 0.032) 0.202(0.091; 0.025)* $t = 2.83$, $p = 0.015$

The numbers of the regions ranging from 1 to 5 represent the frontal, central, parietal, occipital and temporal regions, respectively.
** $p < 0.01$.
* $p < 0.05$.

3.3. EEG power spectra

The 5 min EEG data segments at the beginning and the end of the driving task were chosen for analysis. EEG power spectra were estimated using a 50-order Autoregressive (AR) model with a 100% Hanning window. The relative power was defined as a ratio between the power of each band and the power of the total band, which ranged from 0.25 to 30 Hz. Then, the relative spectra power of the delta band (0.25–4 Hz), theta band (4–8 Hz), alpha band (8–13 Hz) and beta band (13–30 Hz) for each EEG site were calculated. (Relative power is defined as a ratio between the power of each band and the power of the total band, which ranges from 0.25 to 30 Hz.)

Five scalp regions were chosen for EEG Power Spectral Density (PSD) analysis. These regions were the frontal region, central region, parietal region, occipital region and temporal region. The 5 min EEG data segments at the beginning and the end of the driving task were chosen for analysis. Fig. 2 shows the PSD of EEG.

Fig. 2 shows that the PSD of EEG was different at the beginning and the end of the driving task. At the end of the driving task, a peak of PSD near 10 Hz and a small peak of PSD near 5 Hz appeared; the PSD of the delta band increased significantly, but the PSD of the beta band decreased overall. Fig. 3 shows the scalp EEG topography of one subject, including showing the magnitude values for defined frequency bands for the different scalp regions. All PSDs of EEG were normalized by the maximum value of each band. The values were color-coded and plotted to produce a continuous color map. Fig. 3 shows increasing activity in alpha, theta, and delta bands and decreasing activity in the beta band at the end of the simulated driving task. The same trends existed for the other twelve subjects.

When the relative power of each electrode was calculated according to the definition mentioned above, the relative power of each region was obtained by averaging the relative power of the electrodes that were included in this region. The results are presented in Table 1.

Table 1 shows that the general trend of the relative power increased in theta and alpha rhythms, but decreased in beta rhythm, at the end of the driving task. Theta rhythm increased significantly in the frontal ($p < 0.05$), central ($p < 0.05$) and occipital ($p < 0.05$) regions, while alpha rhythm increased significantly in the central ($p < 0.05$), parietal ($p < 0.05$), occipital ($p < 0.01$) and temporal ($p < 0.05$) regions. Beta rhythm decreased significantly in the frontal ($p < 0.05$), central ($p < 0.05$) and temporal ($p < 0.05$) regions. However, there was no statistically significant change in the delta rhythm in all regions.

Table 2
Mean (Std deviation; Std error mean) values of amplitude and latency during the beginning and the end of the driving task for P300.

Component	Location the beginning the end value of t and p
Amplitude (uv)	Fz 13.10(7.54; 2.09) 9.01(5.87; 1.63)** $t = 4.79$, $p < 0.001$
	Cz 12.97(5.68; 1.58) 10.60(6.19; 1.72)* $t = 2.53$, $p = 0.027$
	Pz 14.27(3.79; 1.05) 14.04(5.01; 1.39) $t = 0.27$, $p = 0.79$
Latency (ms)	Fz 363.23(32.40; 8.99) 368.62(27.93; 7.74) $t = 0.68$, $p = 0.51$
	Cz 367.08(32.78; 9.09) 366.46(36.93; 7.47) $t = 0.09$, $p = 0.93$
	Pz 366.31(20.70; 5.74) 373.54(24.93; 6.91) $t = -1.66$, $p = 0.12$

Fz, Cz and Pz are the EEG electrodes located in the frontal, central and parietal brain regions; z means zero, a reference to an electrode placed on the mid-line.
** $p < 0.01$.
* $p < 0.05$.

3.4. ERP analysis

The P300 amplitude at the Fz, Cz and Pz electrodes sites was calculated using the base-peak method that searches within a window from 300 to 800 ms for the maximum positive segment average of 100 ms and subtracted the pre-stimuli 100 ms baseline to obtain base-peak measures. The midpoint of the maximum positive segment was defined as the P300 latency. Fig. 4 shows the P300 waveform of one subject pre-driving and post-driving.

As shown in Fig. 4, the latency of P300 slightly increased after simulated driving, but the amplitude of P300 decreased. The statistical calculation results also supported this conclusion (Table 2).

The latency of P300 did not show a significant difference with driving time at difference electrode locations. The amplitude of P300 decreased significantly at the Fz and Cz locations.

3.5. ApEn and HRV of ECG

The 5 min ECG data segments at the beginning and the end of the driving task were chosen for ApEn analysis. ApEn, which has been used to analyze biosignals, was first introduced by Pincus and is a method to measure the regularity of a time series (Pincus, 1991). As a useful signal for understanding the status of the autonomic nervous system (ANS), HRV is a powerful means to observe the interplay between the sympathetic and parasympathetic nervous systems. It usually uses high-frequency (HF: 0.15–0.40 Hz) power spectra as an index of parasympathetic activity and low-frequency (LF: 0.04–0.15 Hz) power spectra as an index of sympathetic and parasympathetic activity (Kleiger et al., 2005; Bilchick and Berger, 2006).

The ApEn of ECG and HRV power spectra of HF and LF were calculated. The first 10 sec of each ECG segment was chosen as referenced data. The ApEn of continuous 30 s ECG was calculated using 0.4 s stepping. The ApEn of ECG could be obtained by averaging the 30 s ECG. Fig. 5 shows the ApEn curve versus time for one subject.

The paired t-test result showed a significant difference in the mean value of ApEn between pre-driving and post-driving ($t = -4.49$, df = 12, $p = 0.001$). The ApEn mean increased from 0.33 (Std deviation = 0.04; Std error mean = 0.01) at the beginning of the driving task to 0.37 (Std deviation = 0.06; Std error mean = 0.02) at the end. This result indicates that the simulated driving task leads to an increase of ECG ApEn.

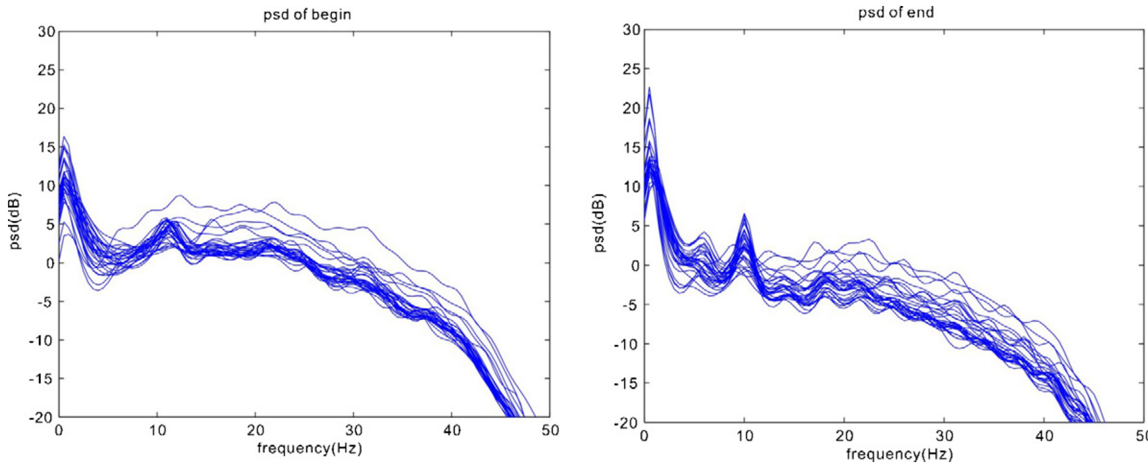

Fig. 2. A representative power spectral density at the beginning and the end of the driving task of one subject.

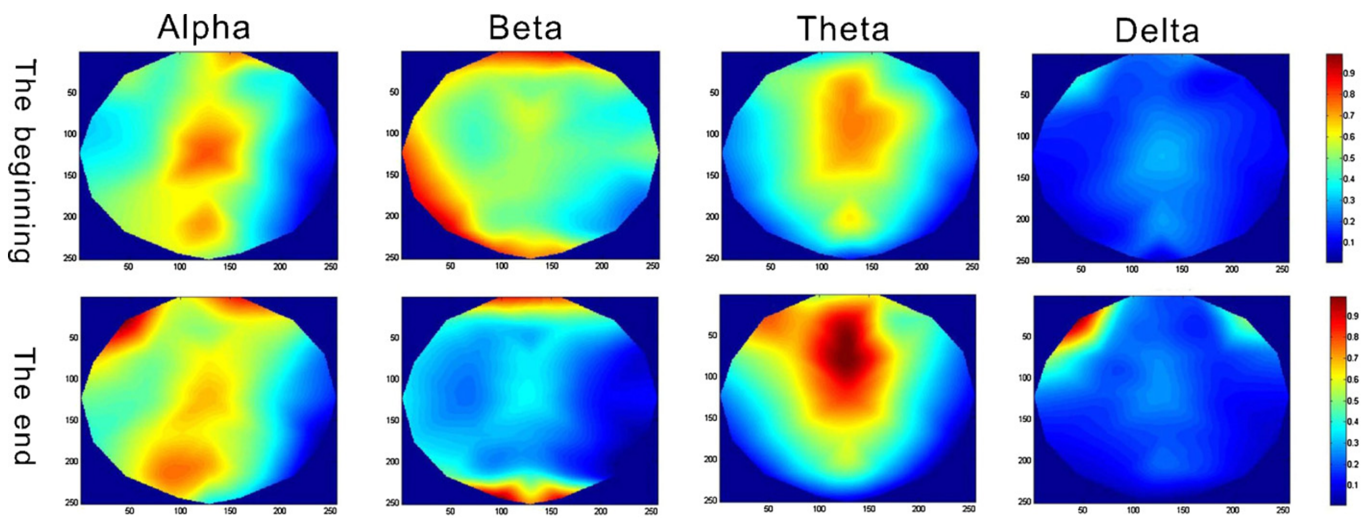

Fig. 3. Scalp topography of electroencephalogram activity. (The oval topography depicts a view from above the head. The blue color indicates a reduction or lack of activity in bands, and the red color indicates more activity in bands.). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

HRV signal was obtained by measuring the R peak from the ECG accurately based on the wavelet transform technique introduced by Li et al. (1995). Fig. 6 shows the original ECG and HRV signal of one subject.

The PSD of HRV was estimated using an AR model (see Fig. 7). The PSD of HRV was divided into low frequency, from 0.04 to 0.15 Hz, and high frequency, from 0.15 to 0.4 Hz. Comparing the data at the beginning and the end of the driving task, the PSD of HRV in low frequency was significantly different ($t = -3.1$, df = 12, $p = 0.009$); the mean power (relative quantity) increased from 732.7 (Std deviation = 434.44; Std error mean = 120.37) to 1057.5 (Std deviation = 637.42; Std error mean = 176.81). Simultaneously, the PSD of HRV in high frequency was also significantly different ($t = 2.32$, df = 12, $p = 0.039$). In contrast to the low frequency, the mean power of high frequency decreased from 859.03 (Std deviation = 77.4; Std error mean = 214.84) to 626.18 (Std deviation = 54.1; Std error mean = 150.06). These results indicate that long-term driving leads to a decreased trend of PSD of HRV at low frequencies and an increased trend of PSD of HRV at high frequencies.

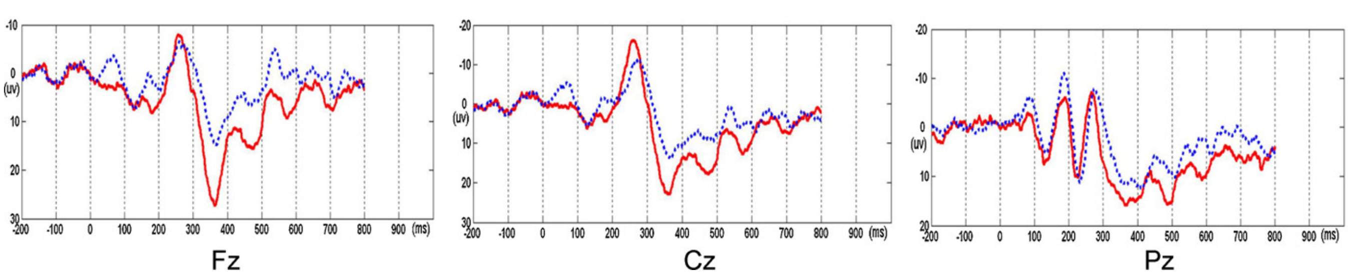

Fig. 4. ERP waveform of Fz, Cz and Pz electrodes (The red solid line represents P300 before driving, and the blue-dashed line represents P300 after driving). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

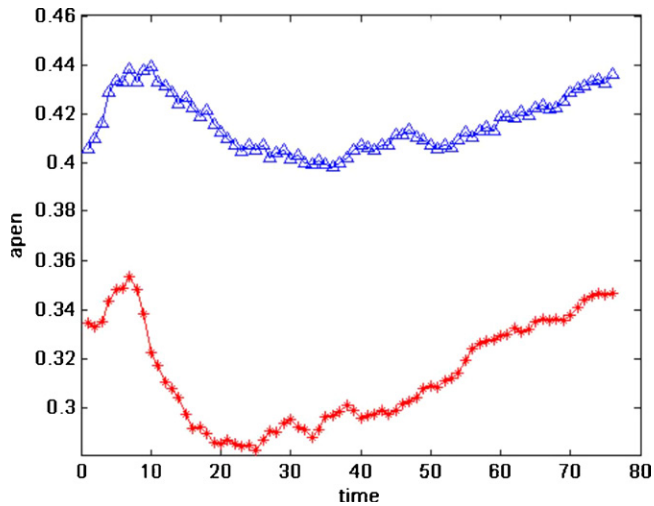

Fig. 5. ApEn curve with time course. (The red solid line represents pre-driving and the blue dotted line represents post-driving). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

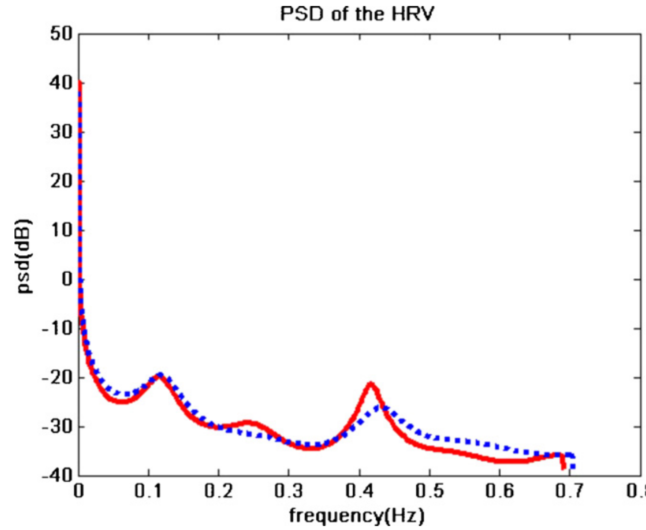

Fig. 7. PSD of HRV of one subject. (The red represents pre-driving, and the blue represents post-driving). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

4. Discussion

In this study, thirteen students of Xi'an JiaoTong University completed the simulated driving task using a monotonous and repetitious highway scene that was designed in a VR-based laboratory. Compared with real-world driving, the subjects were faced with a fewer number of events and amount of overall information to be processed. The reduced stimulation in the driving simulator could lead to performance decrements much earlier (George, 2000). According to the self-reports of subjects, the response time to stimuli and the statistical analysis results of EEG and ECG, it is obvious that the 90 min driving task could induce mental fatigue in the subjects.

Mental fatigue is thought to be associated with reduced efficiency and alertness, prolongation of cognitive information processing, difficulty with concentration, impaired mental performance, etc. The increase in RT to stimuli after the driving task should be associated with driving mental fatigue, which is evident by subjective self-report measures. Some researchers proposed an Asynchrony Model based on MEG and fMRI. They found the extent of neural asynchrony was proportional to the conditioned foot reaction time to visual events while in a driving-like scenario (Bowyer et al., 2009; Hsieh et al., 2009). Whether the longer RT to the Oddball task in our study can be explained by the Asynchrony Mode needs to be verified by further investigation.

It has been known for many years that the change in brain arousal involves specific changes in oscillatory brain activity, and the EEG can reflect the fluctuation of alertness level. The EEG signal may be one of the most predictive and reliable indices to assess mental fatigue. Studies have reported that the alpha power increased when driving mental fatigue occurred (Schier, 2000; Lal and Craig, 2002). In this study, the relative power of all bands except the delta rhythm showed statistically significant differences between the two timepoints ($p < 0.05$). The relative power of the alpha and theta rhythms significantly increased, while the relative power of the beta rhythm significantly decreased in different scalp regions. Okogbaa et al. (1994) pointed out that beta waves were associated with increased alertness and arousal; alpha waves occurred during relaxed conditions, at decreased attention levels, and in a drowsy, but wakeful, state; and theta waves mainly occurred during the sleep state. Gevins and Schaffer (1980) hypothesized that the magnitude of alpha activity during cognitive tasks was inversely proportional to the number of cortical neurons recruited into a transient functional network for task performance. According to the previous findings and hypotheses, the increase of alpha power might indicate that the number of activating cortical neurons is decreasing with simulated driving duration. The increase of theta power is a sign of sleep onset. The decrease of beta power implies that brain arousal level declines. So, the EEG rhythm

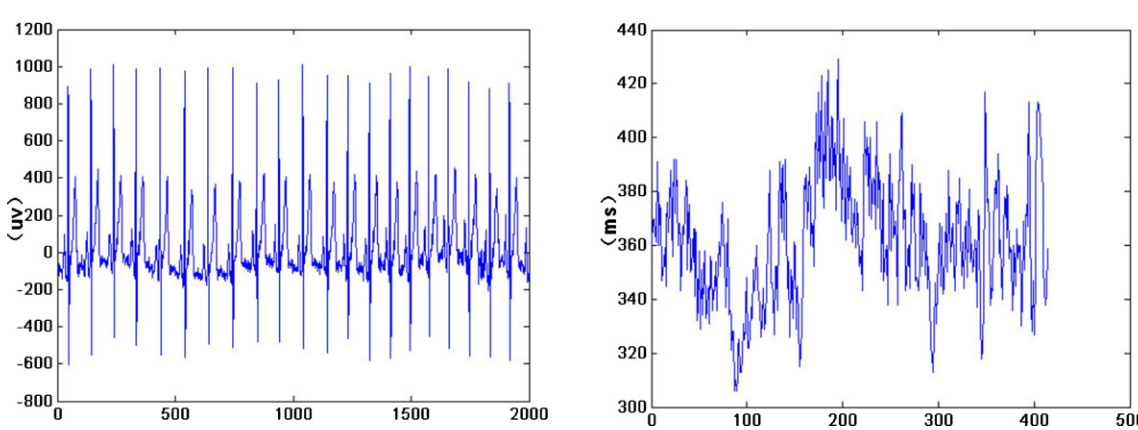

Fig. 6. Original ECG and HRV signals of one subject.

fluctuating tendency objectively reflects the mental fatigue induced by long-term driving and may be a sign of driving mental fatigue. However, there are different EEG rhythm changes on different scalp regions. Jap et al. (2009) investigated four EEG frequency bands and four algorithms to assess driving fatigue. They found significant differences in these parameters at the end of the monotonous driving session, but the variations were not the same for all scalp regions. Some brain regions are of particular importance in maintaining the primary driving performance task of event detection during a secondary conversation task. Several researchers have confirmed this conclusion using both fMRI and MEG methods (Bowyer et al., 2009; Hsieh et al., 2009). Maybe the increased important of a subset of brain regions is a good explanation for the EEG rhythm changes on different scalp regions.

Mental fatigue can result in the decline of arousal level and affect cognitive information processing. Murata et al. (2005) pointed out that the P300 components were useful to identify the depth of cognitive information processing. The prolonged latency indicated that the delayed cognitive information processing and decreased P300 amplitude were related to the decreased activity of cognitive information processing. This study shows that the P300 amplitude significantly decreased at the end of the driving task, which indicates a decrease of the subject's attention level when mental fatigue is induced by the simulated driving task.

Previous studies have reported that heart rate was the most sensitive cardiovascular index of workload and fatigue associated with driving a vehicle (Apparies et al., 1998). In physiology, the autonomic nervous system, including the sympathetic and parasympathetic nervous systems, controls the cardiovascular system. Human heart rates will violently fluctuate during a mental stress situation. High values of ApEn imply high fluctuations in heart rate. The increasing ApEn of ECG at the end of the driving task indicates strong heart rate fluctuations. Heart rate is primarily controlled by the autonomic nervous system and can be increased by shifting sympathovagal balance during driving mental fatigue. HRV signal also has become an interesting and useful tool to analyze cardiovascular autonomic control. Hartley et al. (1994) examined physiological and psychological changes for truck drivers using HRV. They showed that the power mid-frequency sinus arrhythmia tended to increase with driving time and suggested this could be a sign of mental fatigue. The excitability of the sympathetic and parasympathetic nervous systems controls and regulates the automatic nervous function, and this effect can be evaluated by analyzing PSD features of the HRV signal. The PSD of HRV includes two parts: the low-frequency (LF) band (0.04–0.15 Hz) and the high-frequency (HF) band (0.15–0.4 Hz). The LF band is regulated by the sympathetic nervous system and the HF band is regulated by the parasympathetic nervous system. The sympathetic and parasympathetic nervous systems control the balance of the cardiovascular system. In general conditions, the sympathetic nervous system usually works in a tense status. The parasympathetic nervous system works in states of mental peace, and thus the physiological response will be opposite to the sympathetic nervous system. This study shows that the power of the LF significantly increases, and the power of the HF decreases, after a 90 min driving task. The evidence implies that the predominant activity of the autonomic nervous system of subjects turns to sympathetic activity from parasympathetic activity after the task.

Although physiological indicators were found to be associated with the increase in driving mental fatigue, the relative invasiveness and inability of accurately detecting the fatigue is still very challenging for the continuum of driving behaviors and different sources of signal noise and artifacts. Recently, some new driver fatigue detection methods have been developed. Zilberg et al. (2007, 2009) designed a hybrid system for detecting driver drowsiness using piezofilm movement sensors integrated into the car seat, seat belt and steering wheel. They found that driver drowsiness was strongly associated with increases in the EEG alpha band power percentage and reduction in the seat movement magnitude. Maybe combining physiological indicators with these parameters of drivers' operations can potentially serve as a foundation for designing the practical, robust and non-invasive vehicle-based fatigue countermeasure device.

5. Conclusion

In this study, physiological methods were employed to measure mental fatigue during a simulated driving task. For all thirteen subjects, the relative power spectra of different EEG rhythms, the amplitude of P300, and the ApEn of ECG and PSD of HRV showed statistically significant differences before and after long-term driving. It is found that the alpha and theta rhythms increase, and beta rhythms decrease, which indicates that the arousal level declines when mental fatigue occurs. The decrease of the P300 amplitude implies a reduction in the level of attention. Driving mental fatigue also impacts the function of the central nervous system, which consequently controls and regulates the cardiovascular system. The analysis of ApEn of ECG and PSD of HRV strongly support this interpretation.

Although some valuable findings involving physiological measurements were obtained, there are several limitations in this study. First, the number of participants in the experiment is small. According to sample estimation criteria (Ni, 2000), we need at least 30 subjects to yield a statistically significant test ($\alpha = 0.05$, double; power of test $1 - \beta = 0.9$). Second, no controls were included for subjects who have done some other task totally unrelated to driving; the physiological measure of mental fatigue may not be specific to driving. In future studies, the sample size should be increased in order to preferably reduce inter-subject differences. At the same time, a control group for some other task should be considered in the design of the experiment in order to find more reliable physiological measurements for driving mental fatigue. Because the physiological measurements are able to estimate driving mental fatigue induced by driving in a simulator sensitively and objectively, this may be a pilot study for driving safety.

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