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Research on Estimation of Driving Behavior Based on EEG Signals

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Abstract: ***Alertness is ability to measure people's attention in a certain time. And the alertness can be estimated by observing the response time and sensitivity of person who doing tasks for a long time. In a lot of research, a lack of alertness has been implicated as a major factor in road accidents. We first build a simulated driving platform using Unity3D and collect 10 EEG signals from frontal and occipital regions and information of simulated driving offset. Then, we get moving-averaged power spectral with EEG signals by the sliding window technique, calculate the correlation with the driving offset, and find the highest correlation of channels is FP1, POZ and OZ. Finally, we extract features by principal component analysis, construct regression models, and predict simulated driving offset. The result shows that the behavioral data can be simulated by EEG signals and the alertness status can be tested by EEG signals, when the drowsy state of subjects appears more concentrated.***

Keywords: Alertness, EEG signals, Behavioral data, Regression model

1. Introduction

In the recent years, the frequency of road traffic accidents is increasing with the increase in the number of private cars. According to incomplete statistics, there are about 200 thousand traffic accidents in our country every year since 2015, and the number of deaths is approximately 60 thousand. Statistical results of traffic accidents indicate that driver drowsiness during driving is a major causal factor in road traffic accidents [1].

Alertness can reflect the operator's sensitivity to external stimuli for a long time when performing certain tasks, and it is an important indicator to detect whether a driver is drowsy[2]. Nowadays, many methods have been proposed to detect changes in the level of alertness, which are mainly divided into subjective detection methods and objective detection methods. And subjective detection methods are usually auxiliary methods in experiments to detect the state of alertness, such as Karolinska Sleepiness Scale (KSS) [3] or Stanford Sleepiness Scale (SSS) [4]. Objective detection methods mainly include expression-based features, physiological signals, and behavior-based features [5]. And the most used methods are to analyze the behavior of drivers with video technology and to detect physiological changes with electroencephalographic (EEG) activities. But, the video technology requires that the head of subject cannot move freely, and the collection of video in night is difficult [6]. Many researchers choose the EEG-based method to detect the level of alertness, and we use it to study.

EEG signals were widely used in estimating alertness, and Chin-Teng Lin [7] collected EEG data and behavioral data, and analyzed 30-channel EEG data to estimate driver's drowsiness level. We developed a simulated driving platform for experiments, recorded EEG signals and information of simulated driving offset to estimate subject's alertness. In order to ensure the convenience and long-term wearing comfort of EEG experiments, we chose 10-channel EEG signals located at the frontal area and the occipital area to estimate the state of subject's alertness and research the relationship between EEG signals and driving behavior.

This paper is structured as follows. In Section 2, we give a description of experiments setup, including the information of the subjects, unity3d-based driving platform and data collection. Section 3 introduces the analysis methods, including the data preprocessed about the EEG data and the behavioral data, power spectral analysis, correlation analysis, and feature extraction. Section 4 presents the results about the correlation between the EEG spectrum and behavioral data and EEG-based driving behavioral data estimation. Finally, we conclude our finding in section 5.

2. ExperimentsSetup

2.1 Subjects

Experiments were performed in 5 volunteers including students and teachers, and subjects had a 5-minute practice to familiarize themselves with driving tasks and operation steps of the simulated driving platform before the experiment. In order to better study the state of alertness of subjects, experiments should be conducted at the time when subjects were tired and drowsy. Statistical reports indicated that different subjects have different drowsy time, and the drowsiest time also occurs during the early afternoon hours [8]. So, in this study, the time for starting the simulation driving experiments is the afternoon hours after lunch within an hour of continuous driving. Each subject has signed an informed written consent with the adequate understanding of the procedure of the experiment.

2.2 Unity3d-based Driving Platform

In this study, we developed a simulation driving platform to simulate the highway driving scene using the Unity3D software. Fig. 1 shows the Unity3D-based driving scene. The driving scene consisted of some models of objects including roads, desert, hills, trees, and cars. And we set up the speed, form, and direction of the car among these objects and built a highway simulated driving scene of full functionality with the aid of the C# programming language. The driving scene including four lanes from left to right appears cyclically as subjects are driving the car on the road. In order to simulate

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the consequences of a real road surface, during the driving, the car controlled by the subject will be randomly drifted away from the center of the third lane of the road and some driving cars in reverse direction will appear randomly on the opposite lane. Subjects need to keep the car at the middle of the third lane of the road by controlling with the steering wheel.

Figure 1: Unity3D-based simulation driving platform

2.3 Data Collection

The simulated driving software communicated with the NeuroscanNuAmpsExpress system. Because of the convenient limitation of wearable electrode cap, we chose 10-channel EEG signals located at FP1, FP2, PO5, PO3, POZ, PO4, PO6, O1, OZ and O2 with reference electrode placed at the vertex (CZ), as shown in Fig. 2. And the EEG signals and events information including event type and time were continuously recorded using Curry 7 software. To ensure that subjects easily became drowsy, the driving experiment duration was 1 hour at a sampling rate of 1000 Hz. During the experiment, the behavioral information containing time, driving positions, and events was recorded in txt format using Unity3D software.

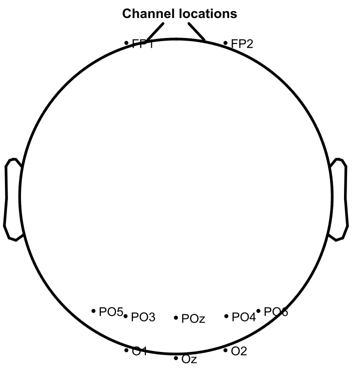

Figure 2: Electrode names and positions on the head

3. Analysis Methods

Our object is to estimate the driving performance of subject based on the EEG signals, and the flowchart of data analysis was shown in Fig. 3. Firstly, for each subject, the EEG data and the behavioral data were processed synchronously through the time of event, and preprocessed respectively. Then, we calculated the moving-averaged log power spectra of 10-channel EEG signals, and the correlation coefficients between the behavioral data and the log power spectra at each frequency of 1-40 Hz. And we selected 3 EEG channels with the highest correlation coefficients to further research using principal component analysis (PCA) algorithm to extract features. Finally, we built the regression model with the first 31 PCA components to research the relationship between EEG signals and driving behavior and estimate the state of subject's alertness.

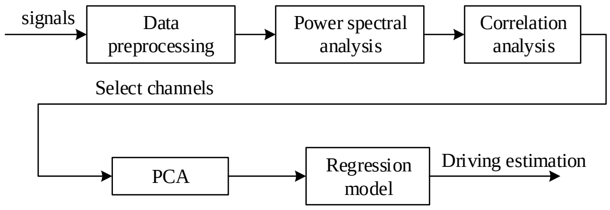

Figure 3: Flowchart for processing the EEG signals

3.1 Data preprocessed

3.1.1 EEG data preprocessed

EEG data is susceptible to noise interference during the collection process, so it is important part to preprocess for EEG data. To remove the noise and better observe the characters, the EEG data first preprocessed using a lowpass filter with a cut-off frequency of 40 Hz. And for each subject, the EEG data was simply down-sampled to 250Hz to reduce calculation costs.

3.1.2 Behavioral data preprocessed

During the driving, the car was randomly drifted away, and the driving position was the original behavior data of the subject, as shown in Fig. 4. We took the average of the driving positions of the subject, deleted data points with the variance greater than 3 between the driving positions and the average, took the average of new driving positions, and calculated the deviation value of the driving positions as behavioral data of the subject, as shown in Fig. 5. Since the period of change in human alertness exceeded 4 minutes, the behavioral data was accomplished using a 90s window with 2s overlap, and the data of each window was calculated the average as moving-averaged behavioral data.

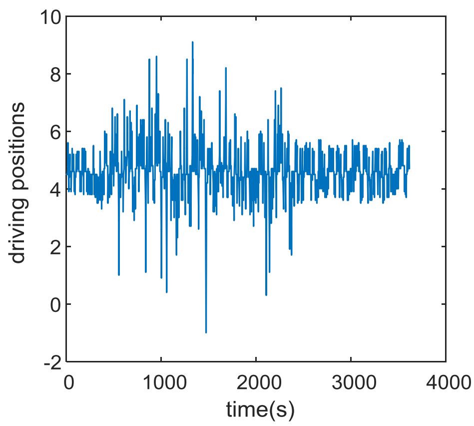

Figure 4: The original behavior data of a subject

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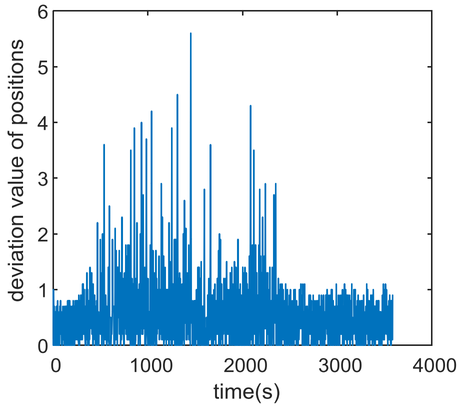

Figure 5: behavioral data of the subject

3.2 Power spectral analysis

There is a close relationship between the state of alertness and the power spectrum of the EEG signals [10]. Moving-averaged spectral analysis of 10-channel EEG data was accomplished using two Hanning windows. The data was first divided using 750-point Hanning window with 500-point overlap. The 750-point epochs were divided using 125-point Hanning window with 25-point step size, and each window extended to 256-point by zero padding [10]. Then, we performed FFT for 256-point, and further calculated the average for 40 frequencies between 1 and 40Hz of all subwindows of each subject respectively. To get the same data length between behavioral data and averaged power spectrum, the data also was accomplished using a 90s window with 2s overlap.

3.3 Correlation analysis

To research the relationship between 10-channel EEG signals and behavioral data, we measured correlation between the moving-averaged power spectrum and driving behavioral data, and got the subject's correlation coefficients at each EEG frequency expressed as

$$Corr_{xy}=(\Sigma(x-\bar{x})*(y-\bar{y}))/\sqrt{\Sigma(x-\bar{x})^2*\Sigma(y-\bar{y})^2}$$

Through the higher correlation coefficients between the log power spectrum and the driving behavioral data, we selected the channels from 10-channel EEG signals to further calculate.

3.4 Feature extraction

In this study, we used principal component analysis (PCA) to extract features of EEG data. The PCA is a linear transformation that can find the uncorrelated vector by orthogonal transformation [9]. Then, the PCA components for the largest 31 eigenvalues were used as inputs of the linear regression model, and the behavioral data was used as output of model. According to the largest eigenvalues of EEG data and the real behavioral data, we got the coefficients of the regression model and the predicted behavioral data. And the parameters of PCA from the training segments were used to extract features in the testing segments so that all data were processed in the same way. Finally, we would got the predicted behavioral data of testing segments with the coefficients of the regression model.

4. Results and Discussion

4.1 Correlation between the EEG spectrum and behavioral data

To investigate the relationship of power spectrum of EEG data and driving behavioral data, we calculated the correlation coefficients for 40 frequencies between 1 and 40Hz of each subject respectively. Fig. 6 shows the correlation coefficients of a subject between power spectrum of EEG data and driving behavioral data, and these are mainly positive. Then, we calculated the variances of the correlation coefficients at 1-40Hz, and found that the higher variances computed separately at dominant frequency bins 4-7Hz and 27-30Hz, as shown in Fig. 7. In order to estimate continuously the level of alertness in near time and make the collection of EEG signals more convenient, we drew the brain topographic maps of the correlations at dominant frequencies at 4-7Hz and 27-30Hz respectively, as shown in Fig. 8. According to the correlation coefficients shown in Fig. 8, we selected the EEG channels at sites FP1、POZ and OZ to assess the state of alertness of subjects.

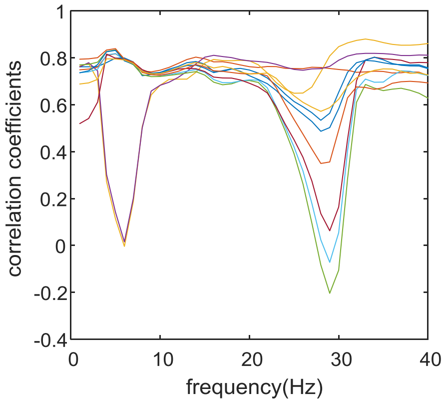

Figure 6: the correlation between EEG power spectrum and driving behavioral data

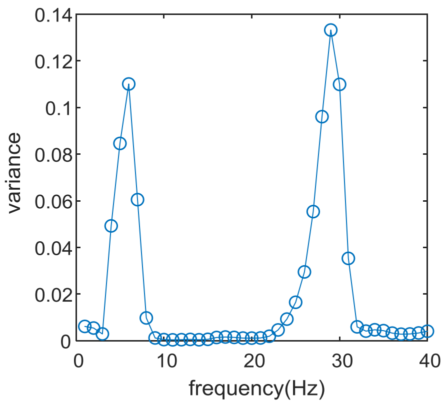

Figure 7: the variance of the correlation coefficients

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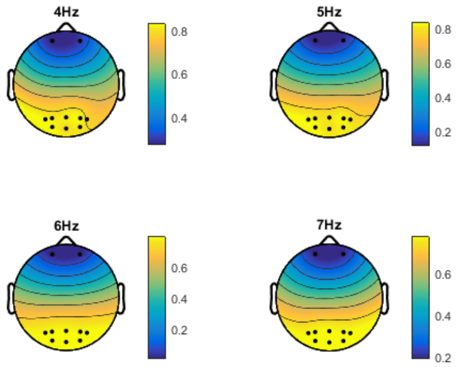
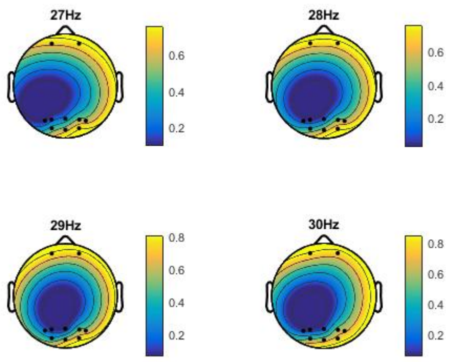


(a) frequencies at 4-7Hz



(b) frequencies at 27-30Hz

Figure 8: The brain topographic maps of the correlations

4.2 EEG-based driving behavioral data estimation

In order to estimate the subject’s driving behavior based on EEG data at sites FP1、POZ and OZ to reduce more unexpected noise. We used the EEG data and behavioral data collected in the first half of each experiment for training, and the data in the second half was used for testing. Then, we further trained a regression model of EEG data and behavioral data using training data, got the predicted simulated behavior data with regression model, and calculated the correlation coefficients between the actual behavior data and the predicted behavior data. Table 1 shows the correlation coefficients of training data and testing data of 5 subjects respectively.

Table 1: The correlation coefficients of the actual and the predicted behavior data

Subject	*Training data*	*Testing data*
1	0.9504	0.7468
2	0.8792	0.6633
3	0.9100	0.5763

As can been seen, the predicted behavior data matched extremely well the actual behavior data in training segments, and the correlation coefficients exceeded 0.87. And in the testing segments, the correlation coefficients were less than 0.6 of the third subject, which was because the state of alertness in the first half and the second half was significantly different during the experiment of 1 hour. Among the testing data of the first and the second subjects, the correlation coefficients were relatively high, and the first subject had the highest coefficient between the actual and predicted behavior data over 0.7. And the subject’s the actual and predicted of behavior data in training and testing segments as shown in Fig. 9. These results suggest that there is a great correlation between behavioral data simulated by the power spectrum of EEG signals and actual behavioral data, and the subject’s driving performance can be estimated by a small number of data channels.

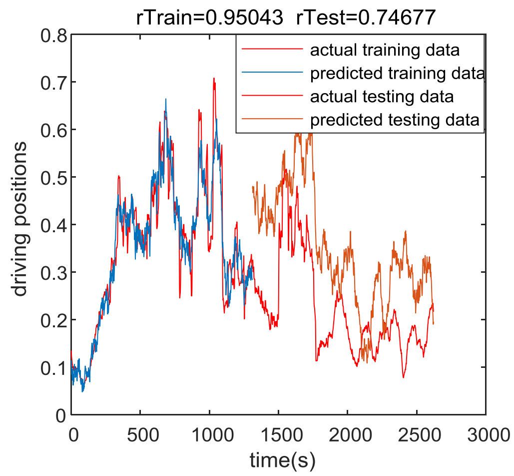


Figure 9: the actual and predicted of behavior data of the subject

5. Conclusion

In this study, we developed a simulated driving platform for highway scenes using the Unity3D software, and designed a driving experiment with 1 hour that the car controlled by subjects was randomly drifted away from the center of the third lane of the road to simulate the real driving situations. In order to ensure the convenience and long-term wearing comfort of EEG experiments, we chose 10-channel EEG signals located at the frontal area and the occipital area to this study, and recorded the car’s driving positions using Unity3D software as behavioral data of subject. Then, the EEG data and the behavioral data were processed synchronously through the first time of event. We combined EEG moving-averaged power spectrum of EEG signals and correlation analysis between EEG power spectrum and behavioral data to select the EEG channels from 10-channel EEG signals. According the correlations, we select the EEG channels at sites FP1、POZ and OZ to assess the state of alertness of subjects. Finally, we combined PCA and linear regression model to estimate the state of alertness and predict the behavioral data of subject by EEG data. Our results demonstrated that the subject’s driving performance can be estimated by a small number of data channels. The methods we used in this study were efficient, and might be used to the system for a real time alertness-monitoring system.

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