Driving Behavior Recognition Based on EEG Data From a Driver Taking Over Experiment on a Simulated Autonomous Vehicle

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Abstract. Driving behavior recognition is a critical part of the driver safety system. Most of the popular researches have utilized the driver’s questionnaire data and driving data to recognize driving behavior. But few studies have used physiological data to recognize different driving behaviors, such as EEG data. In this paper, a new method was presented to recognize different driving behaviors based on EEG data. The driving data and EEG data were collected when participants took over the autonomous vehicle. Through K-means, the driving data were classified into two groups, and the classification results were utilized as inputs to generate a k-Nearest-Neighbor model to recognize driving behavior groups via EEG data. The results showed that the average recognition accuracy was 80.6%, and the highest recognition accuracy was 84.2%, indicating that there is an obvious relation between EEG data and driver taking over behavior.

1. Introduction

Driving behavior recognition has been widely studied in the field of vehicle engineering to improve the efficiency and safety of the automobile [1]. Related researches have shown that driving behavior classification is the key point of developing intelligent driving assistant system. If driving behavior can be identified correctly, the system can send warnings to drivers who have dangerous driving behavior. The driving behavior recognition module can be integrated into the Advanced Driver Assistance System (ADAS). With different modules integrated, the automaticity, safety, and comfort of driving can be improved. Typically, subjective questionnaire data and objective driving data are two prime driving behavior classification indicators. Based on these indicators, driving behavior questionnaires and driving skill inventories were formed for driving behavior recognition [2], [3]. When these studies used subjective questionnaire to classify driving behavior in the early stage, only one or two aspects of driving behavior have been considered in self-reported scales. Therefore, Taubman developed an 8-dimensional driving behavior inventory for driving behavior recognition [4]. However, using subjective questionnaires data to classify driving behaviors can only reflect the driving habits of drivers, which lacks dynamic display of changes in driving behaviors.

Besides subjective questionnaire data, objective driving data collected from driving experiment are also a major data for driving behavior recognition. Recently, smartphones are being used as mobile sensors to collect driving data [5]. Vehicle-mounted GPS can also be utilized as an effective sensors to evaluate driver’s states [6]. However these objective driving data mainly reflect the changes in driving parameters of the vehicle, which are the external results of different driving behaviors. The classification
methods based on driving data focus more on the driving status of the vehicle, and they are insufficient to reflect the driver’s psychological and physiological status. Establishing an effective driving behavior recognition model cannot rely solely on objective driving data. Evaluating the driver’s physiological and psychological status may help improve the recognition performance of driving behavior recognition model.

Compared to subjective questionnaire data and objective driving data, only a small percentage of researchers have used physiological data such as electroencephalography (EEG) to recognize driving behavior. EEG has been proved to be accurate and effective data for physiological status identification [7], [8]. EEG data were used to recognize dangerous driving style, and warnings were sent to the drivers as feedback [9]. Driving is a complex task that requires the brain to play a synergistic role in perception, planning, and control. And EEG patterns in different brain regions can reflect the status of different brain functions. Compared with the other analytical data, EEG data are better in two aspects: (1) EEG data can achieve real-time online feedback recognition results; (2) EEG data can not only reflect kinematic vehicle indicators, but also other information (physiological and psychological).

In this study, a driver taking over experiment on a simulated autonomous vehicle was designed, and a driver’s behavior recognition system was proposed. During the experiment, driving data and EEG data were collected. Based on the EEG data, a suitable recognition system was established to recognize the driving behavior of the driver, and revealed the correlation between EEG and driving behavior.

2. Research Method

The purpose of this study is to develop a driving behavior recognition system using EEG data and verify the recognition results of driving behavior. The research methods of this paper are described as the following three parts: the first part introduces the experimental setup; the second part introduces data acquisition and data processing; the third part describes the method of developing a driving behavior recognition system based on EEG data.

2.1. Experimental Setup

The experiment was performed at Wuhan University of Technology (WHUT) and was conducted following the recommendations of the Helsinki Declaration, and all participants signed a written informed consent. The protocol described the purpose of this experiment, the experimental process, and the experimental cost. The experiment required simulator to build a driving platform, the simulator (G29, Logitech Inc., Fremont, CA) that was chosen in this experiment had a practical driving operation system, such as steering wheel, accelerator pedal and brake pedal (Figure 2). There was a 40-inch screen in front of the simulator to show driving scenario.

Fifteen healthy (8 males and 7 females) participants were recruited for this experiment. Their average age are within 28.21±3.28 years. Their average driving experience are within 4.64±2.55 years, and their average annual mileage are more than 1000 km. Before the experiment officially started, every participant was required to operate the simulator to complete a 15 minutes practicing driving, none of them showed any simulator sickness.

L3 level autonomous vehicle requires to be taken over when driving outside the Operational Design Domain (ODD). It involves the driver’s state switching and requires driver restore the driving state quickly to coordinate driving operations. To study the driving behavior of taking over vehicle, this experiment used a 35 km two-way closed road (Figure 1) as the driving scenario (Figure 3) designed using Unity 3D (Unity Technologies, USA). There are two lanes, each 3.75 m wide. The speed limit is 80 km/h. The traffic flow is sparse, and the weather condition is comfortable. In the experiment, the ego vehicle was kept driving automatically until it was close to the obstacles and had a risk of collision (Time To Collision=7s), then the simulation system sent out warning sound and screen showed text to remind participants to take over the vehicle. Participants needed to switch driving state by touching the paddle in the simulator and controlled the vehicle to avoid collision as soon as he/she heard the alarm.
2.2. Data Acquisition

Driving skills and driving style are two prime factors in measuring the pros and cons of driving behavior [10]. Driving skills are measured by the standard deviation of the driving data, while driving style is measured by the average of the same driving data set [11]. In this experiment, the driving data were collected when participants took over the autonomous car, and the driving data included: velocity, time of vehicle-taking over, the rotation angle of the steering wheel and the angular velocity of steering wheel. The driving simulator was used to collect driving data with a sample rate of 60 Hz. And the data logging function of the simulation system was utilized to record the time of participants taking over the vehicle, and the driving speed.

In this experiment, the EEG signal acquisition equipment was a 64-channel EEG recording analyzer produced by BP (Brain Products, Germany). The EEG recording analyzer usually consists of an EEG signal amplifier and an electrode cap. The BP EEG recording analyzer included an actiCHamp EEG signal amplifier (Figure 4) and a 64-channel wet electrode cap (Figure 5). The electrode cap was utilized to collect EEG signals.

The location of the scalp based on the international 10-20 system (Figure 6). The EEG signals were recorded at a sampling rate of 500 Hz. EEG signals were very weak, which were easily interfered by eye movement or other external interference. Therefore, the experiment has processed EEG signals to remove original noise. The EEGLAB toolbox and MATLAB 2016a were used to process raw data. First, the EEG data were down-sample to 100 Hz, and the noise was eliminated by FIR filter (0.5-30Hz), and
Independent Component Analysis (ICA) was utilized to decompose EEG data. Adjust function (an EEGLAB plugin) was used to remove the components caused by artifacts. Then, the bad channel was relocated by averaging two adjacent channels. Finally, EEG data were used as reference and baseline correction. The Figure 7 shows the example of raw EEG and processed EEG.

2.3. Data Analysis

A driving behavior recognition scheme was proposed (Figure 8). The scheme consisted of two parts: driving behavior definition based on driving data and driving behavior recognition based on EEG data.

In the first part, driving data was considered as effective classification data. Driving data were processed by Z-score, and due to lack of label information, Principal Component Analysis (PCA) was chosen to reduce the dimension of driving data. After these methods, the driving data from 5-dimensional data reduced to 2-dimensional standard Z-scores. The processed data were utilized as input data of K-means. The core formula of K-means is shown below.

\[
ESS = \sum_{k=1}^{K} \sum_{i \in C_k} \| X_i - \mu_k \|^2
\]  

(1)

Where \( X_i \) is an observation of cluster \( C_k \).

In the second part, firstly, the original EEG data were denoised and processed by the FIR filter and ICA method. Secondly, according to the Schwab rule, EEG data within 0.5-30Hz were selected for subsequent analysis. The rule divided EEG into \( \delta \)-band (0.5-4Hz), \( \theta \)-band (4-8Hz), \( \alpha \)-band (8-13Hz), and \( \beta \)-band (13-30Hz). These four different frequency bands of EEG can reflect different human mental
Therefore, when performing EEG feature extraction, the study followed these four frequency bands to extract the EEG feature. The EEG features (amplitude and power spectral densities) were extracted from the processed EEG by using Fast Fourier transformation (FFT) and Welch method [12], [13]. And with the label information obtained from the classification results, Linear Discriminant Analysis (LDA) was utilized to extract the core EEG features. Finally, the core features of the EEG composed matrix $M_L (M_L \in \mathbb{R}^{232 \times 2})$ and the matrix were used as input data of the k-Nearest-Neighbor for driving behavior recognition. The core formula of k-Nearest-Neighbor algorithm is shown below.

$$d_{AB} = \sqrt{\sum_{i=1}^{n} (x_{ui} - x_{ni})^2}$$

(2)

Where $d_{AB}$ represents the Euclidean distance between the test data and the training data.

3. Result and Discussion

3.1. Driving Behavior Definition Based on Driving Data
In this experiment, 232 sets of data from 15 participants were classified by K-means algorithm, and the classification results were generated into a visual figure (Figure 9). The number of K was determined by the calculation results of Sum of Squares due to Error (SSE). The core formula of SSE is shown below.

$$SSE = \sum_{i=1}^{n} \sum_{j=1}^{m} w_{ij} (x^{(i)} - u^{(j)})^2$$

(3)

Where $u^{(j)}$ represents the center of the $j$ category; $x^{(i)}$ represents a sample of the $j$ category.

When the SSE value between adjacent K changed significantly, this K value was the optimal K. The calculated SSE value is shown in Figure 10 below. The K value of the cluster was selected as 2. The original data did not have label information, so the number of iterations needed to be greater than 1, and the experiment ended the iteration until each cluster did not change. It can be seen from the figure that the driving behavior of taking over autonomous vehicle was divided into two categories, and the number of sample points in the two categories was roughly the same (one category has 109 and the other category has 123). The K-means effect was very stable, which meets the experimental classification requirements.

![Figure 9. The location of 64-channel based on the international 10-20 system](image1)

![Figure 10. Raw EEG data and processed EEG data](image2)

The average value and standard deviation of each driving data groups were calculated (Table 1), based on the difference between the average value and standard deviation, and two categories were named as the aggressive group and the conservative group respectively. Analysis of variance (ANOVA) had shown obvious differences in driving data between two driving behavior groups (Table 1, all $P < 0.01$). According to the driving data of different groups, it was obviously found that the driving speed of aggressive group was relatively high after taking over the vehicle, and it was more inclined to adopt turning the steering wheel strategies, and the average time of vehicle-taking over was longer than the conservative group. While conservative group responded quickly after hearing the request of vehicle-
taking over and maintained a relatively stable driving speed in a sparse traffic condition, which means the conservative group preferred a more stable driving behavior.

Table 1. Driving variables of two groups

| Driving variables                      | Aggressive group(n=109) | Conservative group (n = 123) | F/P/η² |
|---------------------------------------|-------------------------|-----------------------------|--------|
| Velocity(Km/h)**                      | 71.9± 5.8               | 64.9±2.2                    | 121.2/0.000/0.67 |
| Time of vehicle-taking over(s)**      | 2.35±0.72               | 0.95±0.21                   | 6.0/0.001/0.17 |
| Rotation angle of the steering wheel(◦)** | 41.3±18.6               | 24.1±5.4                    | 54.3/0.000/0.61 |
| Angular velocity of steering wheel(rad/s)** | 2.64±0.79               | 1.35±0.34                   | 64.8/0.000/0.65 |
| Angular acceleration(rad/s²)**        | 868.5±217.4             | 313.1±114.2                 | 110.7/0.000/0.68 |

*P < 0.01 **P < 0.001

3.2. Driving Behavior Recognition Based on EEG

The original 8-dimensional EEG features were reduced to 2-dimensional core EEG features by using the LDA method, and then these core features were utilized as input data for training the k-Nearest-Neighbor. Table 2 lists the recognition results evaluated by the leave-one-subject-out validation method. The average accuracy was 80.6%, the accuracy and recall of the aggressive group were 77.1% and 83.5%, while the accuracy and recall of the conservative group were 84.2% and 78.1%, respectively. From these data, it can be seen that the accuracy of the recognition based on EEG compared with the accuracy of random recognition (50%) has been significantly improved.

Table 2. Driving variables of two groups

|          | True label | Precision |
|----------|------------|-----------|
| Predicted label | Aggressive | Conservative |          |
|           | 91         | 27        | 77.1%    |
|           | 18         | 96        | 84.2%    |
| Recall   | 83.5%      | 78.1%     |          |

4. Conclusion

This study collected driving data and EEG data when performing the autonomous vehicle-taking over experiments and utilized EEG signals to recognize driving behavior. The results showed that the average accuracy of driving behavior recognition was 80.6% and the highest accuracy was 84.2%. This illustrates that to some extent, the use of EEG to recognize driving behavior is feasible. From the perspective of vehicle-road collaboration, the driver’s physiological and psychological state information can be further applied to the intelligent driving assistance system. The system plays a role in the fields of driver warning, personalized intelligent driving customization, and connected vehicle information transmission. The implementation will improve the safety, comfort and efficiency of vehicle-taking over, meanwhile it also will reduce related driving accidents.

Limited to experimental conditions, this study only conducted driving simulation experiments, and the collected driving data was also limited. There is a certain degree of deviation between the driver’s perception and behavior patterns in simulated driving and real driving. In the future, real vehicle experiments on actual roads may be considered to verify existing research conclusions and correct deviations caused by simulated experimental environments.

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