EEG-Based Detection of Braking Intention During Simulated Driving

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Abstract—Accurately detecting and identifying drivers’ braking intention is the basis of man-machine driving. This paper proposed an electroencephalographic (EEG)-based braking intention measurement strategy. We used the Car Learning to Act (Carla) platform to build the simulated driving environment. 11 subjects participated in our study, and each subject drove a simulated vehicle to complete emergency braking and normal braking tasks. We compared the EEG topographic maps in different braking situations and used three different classifiers to predict the subjects’ braking intention through EEG signals. The results of the experiment showed that the grand-average response time of all subjects in emergency braking was 762 ms; emergency braking and no braking can be well distinguished, while normal braking and no braking were not easy to be classified; for the two different types of braking, emergency braking and normal braking had obvious differences in EEG topographic maps, and the classification results also showed that the two were highly distinguishable. This study provides a user-centered driver-assistance system and a good framework to combine with advanced shared control algorithms, which has the potential to be applied to achieve a more friendly interaction between the driver and vehicle in real driving environment. An earlier version of this work Liang et al. (2022) has been presented as preprint in arXiv (https://arxiv.org/abs/2207.12669).

Keywords—braking intention, detection, EEG, simulated driving, brain computer interface

I. INTRODUCTION

Recently, the application of EEG in the field of driving safety has attracted great attention. These studies can be categorized as drivers’ fatigue, distraction and intention detection. Drivers’ intention studies were mostly about braking intention, and the EEG-based research received the most extensive attention [2-6, 9-11]. In [2], the event-related potentials (ERP) was used by Haufe et al. to detect the driver’s emergency braking intention. The experiment was carried out on a driving simulator. Based on EEG signals, the occurrence of emergency braking can be predicted 130 ms before the driver’s real braking action. Subsequently, Haufe et al. carried out the above experiment in real-world driving, and the experimental results resembled those during simulated driving [3]. The experimental result verified the feasibility of predicting emergency braking intention through EEG signals. Kim et al. investigated neural correlates of braking under various braking situations in simulated driving environment, and results showed that using different EEG features could improve the detection accuracy of braking intention in different scenarios [5]. Teng et al. proposed a new method to predict the intention of emergency braking by EEG signals [6]. Their proposed model combined regularized linear discriminant analysis (RLDA) with spatial-frequency features. The experiment results of 12 subjects showed that the proposed method was effective. Hernandez et al. investigated the feasibility of using drivers’ EEG signals to recognize the intention of emergency braking when a driver experienced cognitive states such as stress, workload, and fatigue. The average recognition accuracy of emergency braking intention was more than 70% in three different cognitive states [4]. Bi et al. improved the accuracy of detecting the driver’s emergency braking intention by combining EEG signals and vehicle’s external environment, which provided a new idea for man-machine driving [11]. The driver’s braking includes not only emergency braking (also known as sharp braking), but also normal braking (also known as soft braking), which is very common during driving. However, the studies on EEG-based detection of driver’s braking intention mainly focused on the field of emergency braking, little attention was paid to the detection of the driver’s normal braking. If different types of braking can be identified before the real braking action, the vehicle will know the driver’s specific braking intention, so as to
take some measures in advance to achieve a more natural and effective human vehicle interaction.

In this paper, we mainly studied whether the driver’s two different types of braking intention (emergency braking and normal braking) can be recognized in advance by EEG, and whether the two can be effectively distinguished. For the sake of safety, we use the simulated driving platform to conduct the experiment. Relevant research showed that in terms of emergency braking intention detection, the simulated driving environment had similar results to the real driving environment [3]. The driving platform simulation adopted Carla, which is an open urban driving simulator [7]. In the experiment, subjects drove a simulated vehicle to complete a series of normal braking and emergency braking tasks during driving. In emergency braking situations, subjects needed to make emergency braking immediately according to the external clues. And in normal braking situations, subjects spontaneously completed the braking action without external clues. EEG signals of the subjects were recorded synchronously. Then we used the classification algorithms to identify the subject’s braking intention and judged the system’s feasibility.

The rest of this paper was organized as follows. The Methods and Materials section described subjects, experimental setup, data collection, classification algorithm, and performance metrics. The experimental results were shown in the Results section. In the end, we discussed and concluded this study, and described the possible application scenarios of our work.

II. MATERIALS AND METHODS

A. Subjects

A total of 11 subjects (the age ranged from 22 to 36 years, with an average of 25.73 years, including 9 males and 2 females) participated in the experiment. All subjects were recruited from school volunteers, obtained driving licenses and had more than 2 years of driving experience. Each subject had normal or corrected-to-normal vision. All subjects reported no history of neurological diseases. Before the experiment, we explained the purpose and the procedure of the experiment, and all subjects participating in our study wrote informed consent according to the Declaration of Helsinki. Each subject had enough sleep (>=8 hours) before the experiment, and did not take any drugs within three days before the experiment. During the experiment, each subject could end the experimental task at any time without any punishment. If the subject successfully completed the experiment, he/she would be paid 400 RMB.

B. Experimental Setup

As shown in Fig. 1, our experimental platform consisted of a driving simulator (composed of a steering wheel, a gas pedal, a brake pedal, and a driver’s seat), an EEG acquisition equipment (ActiCHamp, Brain products, Germany) and two computers. The EEG acquisition equipment would record the subject’s scalp EEG signals during driving. By using the application program interface (API) of Carla driving simulator, we realized the automatic labeling of the EEG signals. The computers had two functions: (1) as the user interface, presented the driving simulation environment; (2) as the recording device, recorded the EEG signals with labels in real time.

The experiment included two different types of braking situations, one was emergency braking and the other was normal braking. In emergency braking situations, the setup consisted of two virtual vehicles, the vehicle in front (also known as lead vehicle) and the following vehicle. The lead vehicle was controlled by the instructor and the speed was kept at 90 km/h. The following vehicle was controlled by the subject, driving in the same lane, and keeping a distance of 6-12 m from the lead vehicle. The lead vehicle in front would decelerate rapidly at random (the time interval varied from 15 s to 60 s), and reminded the following vehicle through the brake lights. To avoid collision, the subject needed to make emergency braking immediately when he/she saw the front vehicle’s brake lights started flashing. In this process, two moments were recorded through the API of Carla platform, one was the moment when the brake lights of the lead vehicle were on, and the other was the moment when the subject of the following vehicle stepped on the brake pedal. 3 s after the deceleration, the lead vehicle accelerated and maintained 90 km/h. The subject continued to drive the vehicle to follow the lead vehicle, and kept the distance between 6 m and 12 m. The distance between the two vehicles was displayed on the window of the simulation platform, and the subject could see it in real time. In normal braking situations, the experimental setup was similar to that of the emergency braking, except that the lead vehicle always maintained a speed of 90 km/h and did not decelerate randomly. The subject drove the same vehicle on the same road as in the emergency braking situations, and broke every 15-60 s spontaneously and randomly. After depressing the brake pedal for about 3 s, the subject accelerated the vehicle to follow the lead vehicle and kept the distance at 6-12 m. As shown in Fig. 2, each subject needed to complete 5 driving tasks, and each lasting for 30 minutes. After each driving task, the subject rested for 5 minutes.

C. Data Acquisition

In this study, the amplifier and electrodes of Brain products were used to record the subject’s EEG data. The electrode arrangement adopted the internationally accepted 10-20 system, in which 28 electrodes (F3 F4 F5 F6 Fz FC1 FC2 FC5 FC6 F7 F8 T3 T4 T5 T6 T7 T8 O1 O2 Oz) were recorded.
FT8 C3 C4 Cz T7 T8 CP1 CP2 CP5 CP6 P3 P4 P5 P6 Pz O1 O2 and Oz) were used to record data. 2 electrodes (TP9 and TP10) were used as reference electrodes, and 1 electrode (FPz) was the ground electrode. The resistance of all electrodes were kept below 10 kΩ. The EEG data acquisition sampling rate was set to 200 Hz. We only carried out a simple preprocessing of the EEG data in this paper. First, a bandpass filter of FIR with a low-frequency of 1 Hz and a high-frequency of 45 Hz was used to filter the original signals. Then, the processed signals with an amplitude greater than 300 μV were eliminated. The EEG signals corresponded to three kinds of situations: emergency braking, normal braking and no braking. In normal braking and emergency braking situations, we intercepted the target epochs ranged from -3000 ms to 1000 ms relative to the moment when the subject started braking. The no braking epochs were extracted by sliding a window (4000 ms length) on the EEG signals which were more than 3000 ms away from any subjects’ braking behavior. Epoch-wise baseline correction was performed by subtracting the average of the first 500 ms EEG potentials. In total, we got 189 ± 54 epochs in emergency braking and 114 ± 27 epochs in normal braking per subject, respectively. In addition, we randomly selected 200 epochs of no braking data from each subject through the sliding window.

D. Classification Algorithms

We selected three commonly used representative algorithms in the field of brain computer interfaces (BCI), which were Common Spatial Patterns combined with Linear Discriminant Analysis (CSP+LDA) [12], Riemannian Minimum Distance to Mean (RMDM) [14], and the EEGNet algorithm based on deep learning [8]. As a traditional EEG classification algorithm, CSP+LDA algorithm has very good performance and is widely used in different types of BCI [13]. Algorithms based on Riemannian Geometry have changed some of conventions used in traditional approaches. Riemannian Geometry classifiers (RGCs) do not estimate the optimal filter, but map the EEG data directly to the geometrical space, which has suitable metrics for classification. Despite their short time in EEG decoding, RGCs have received extensive attention in BCI, including the winning score obtained in five recent international BCI competitions [13]. Using the training data, RMDM classifier calculates the geometric mean of each class, and then assigns test data to the class closest mean. RMDM is a simple yet efficient classifier, and has been reported to result in a high classification accuracy [15]. EEGNet is a compact convolutional neural network specially designed for EEG classification. It has the advantages of simple structure, short training time and high classification accuracy. More importantly, EEGNet is an end-to-end classification method, which can be conveniently used for online classification.

There were three categories: emergency braking, normal braking and no braking. We conducted comparative classification studies in three different combinations, namely, emergency braking vs. no braking, normal braking vs. no braking, and emergency braking vs. normal braking. For each subject, we trained the classifier respectively. The number of epochs in the three categories was not equal. We chose epochs of the other two categories based on the category with the least epochs, so that each subject had the same number of epochs in the three categories. The length of the EEG data input to the classifier was 1000 ms. We used the EEG data of 1000 ms before braking to train the classifier, and adopted a sliding window with a length of 1000 ms to get the data for testing. For each subject, a total of 10 times of training and testing were carried out. Each time, we randomly selected 50% of the extracted epochs as the training set and the rest as the test set. We calculated the average of 10 times as the final result.

E. Performance Metrics

We used the prediction time and its corresponding classification accuracy to measure the system’s performance. The $p$ was the classification accuracy rate, which was defined as the ratio of correct classification number $N_c$ to the total amount of data $N$. The prediction time was defined as how long the classifier can recognize the subject’s braking intention at a certain accuracy before the subject stepped on the brake pedal.

III. RESULTS

A. Emergency braking response time

Emergency braking response time (EBRT) was the duration from the moment when the lead vehicle’s brake lights started flashing to the moment when the subject started to step on the brake pedal under an emergency braking situation. In our experiment, the average EBRT was $762 ± 156$ ms, the maximum was $1490$ ms, and the minimum was $300$ ms. EBRT’s distribution percentiles were $P_{25}=520$ ms, $P_{50}=660$ ms, $P_{75}=750$ ms, $P_{90}=850$ ms, and $P_{95}=1020$ ms.

B. The EEG Topographic Map

Fig. 3 showed the EEG topographic maps with an interval of 100 ms from 1000 ms before braking to the onset of braking. Subfigures (a) and (b) were obtained by subtracting the no braking epochs from emergency braking and normal braking respectively. Subfigure (c) was obtained by subtracting normal braking epochs from emergency braking. 0ms represented the onset of braking. The warmer the color, the higher the potential of EEG signals. From 400 ms before emergency braking, the EEG potential started to rise significantly in the occipital area, and the maximum potential was approximately 6uV reached at about 300 ms before subjects’ braking action. We believe that this potential is similar to P300, which was also induced by the random flashing stimulation similar to the oddball paradigm. From 200 ms before braking, the central region of the brain (mainly responsible for movement) began to have a negative potential offset, which showing the subject’s motor preparation potential for emergency braking. Compared with emergency braking, the EEG changes of normal braking were relatively flat. From 900 ms to 400 ms before normal braking, there was a small negative potential offset in the central region of the brain. No significant potential changes were found in the occipital region, which is mainly responsible for the processing of visual information. A comparison of the EEG topographic maps under emergency braking and normal braking was also conducted, as shown in subfigure (c). We can see that obvious differences in EEG potential between the two braking modes, indicating that emergency braking and normal braking are significantly different in cognitive processing. This also provides some physiological basis for classifying emergency braking from normal braking.

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Fig. 3. EEG topographic maps. -1000 ms represents 1000 milliseconds before the subject started braking, and 0ms is the onset of braking. The warmer color indicates the higher values of EEG potentials.

Fig. 4. Classification accuracy curves for detecting braking intention. 0 on the Time axis represents the onset of braking. The results were obtained through a sliding window of length 1000 ms, and the accuracy of classification corresponds to the end point of the window.
C. Classification Performance

Fig. 4 showed three sets of classification accuracy curves of different algorithms for detecting two different types of braking intent. Subfigure (a) showed average accuracy curves of emergency braking vs. no braking, subfigure (b) showed average accuracy curves of normal braking vs. no braking, and subfigure (c) showed average accuracy curves of emergency braking vs. normal braking. Three different classification algorithms, CSP+LDA, RMDM and EEGNet, were used respectively. The EEG data of subjects 1000 ms before braking were used to train classifiers. The test data was obtained through a sliding window of length 1000 ms, and the accuracy of classification corresponded to the end point of the window. The classifiers for each subject were trained and tested respectively, and the average values of all subjects were taken to generate the accuracy curves shown in Fig. 4. We got the following results:

- Emergency braking and no braking can be well distinguished. At the braking moment, the average accuracy of CSP+LDA, RMDM and EEGNet algorithms were 88.85 ± 10.02%, 94.97 ± 2.85% and 91.91 ± 3.39% respectively; 100 ms before braking action, the average accuracy were 86.99 ± 10.89%, 86.39 ± 5.64% and 84.66 ± 5.96% respectively.

- The classification results of normal braking vs. no braking were poor. At the moment of braking, the average classification accuracy of CSP+LDA, RMDM and EEGNet algorithms were 58.14 ± 8.57%, 65.35 ± 7.74% and 61.06 ± 5.58% respectively; 100 ms before braking action, the classification accuracy were 58.42 ± 8.43%, 62.45 ± 6.43% and 59.94 ± 6.40% respectively.

- Two different braking modes (emergency braking and normal braking) can be effectively distinguished. At the braking moment, the average classification accuracy of CSP+LDA, RMDM and EEGNet algorithms were 87.57 ± 10.96%, 95.59 ± 4.25% and 90.84 ± 5.74% respectively; 100 ms before braking, the accuracy were 86.01 ± 11.26%, 89.03 ± 6.81% and 85.64 ± 7.29% respectively.

- When the test data selected by the sliding window were consistent with the training data in time, the RMDM based on Riemannian Geometry achieved the higher average classification accuracy than other algorithms in all three classification cases. When the test data selected by the sliding window were not inconsistent with the training data in time, such as when the test data was 200 ms ahead of the training data, CSP+LDA algorithm had a comparative advantage. EEGNet is a deep learning-based classifier, which requires a large number of training samples. We trained the classifier of each subject separately in this paper, and the classification result of EEGNet was not as good as RMDM.

IV. DISCUSSION AND CONCLUSION

This paper mainly investigated whether the braking intention can be detected by the driver’s EEG signals while driving. We conducted experiments on a simulated driving platform and collected EEG data of 11 subjects. Two different types of braking intention were analyzed. We carried out EEG topographic maps for comparison, and used three classifiers to detect the subject’s braking intention. Through the analysis of EEG topographic maps, we found that compared with normal braking, the EEG changed significantly before emergency braking. The reason may be that under normal braking situations, the subjects took a spontaneous and relatively gentle action, while under emergency braking situations, the subjects had a sense of tension after the stimulation and needed to complete the braking behavior as soon as possible. The classification results also proved our conjecture that it was easier to detect the intention of emergency braking. At time 0 relative to the onset of braking, RMDM algorithm achieved the highest average classification accuracy of nearly 95%. Even 200 ms before emergency braking, CSP+LDA still achieved an average classification accuracy of about 83%. For the detection of normal braking intention, the result of RMDM was about 65% at the moment of real braking action, but only about 60% 100 ms before braking. For this classification algorithm, the Riemannian Geometry-based RMDM algorithm had the best classification results, but CSP+LDA algorithm showed advantages in early braking intention detection. Due to the lack of a large number of training samples, the EEGNet algorithm based on deep learning did not achieve excellent classification results. The challenge of insufficient samples needs to be solved when using deep learning methods in the field of EEG classification.

Our work mainly focuses on the detection of emergency braking intention from normal driving and normal braking, and provides users with a good shared control framework. When a user is faced with a sudden driving situation, he/she may make mistakes due to nervousness. Theoretically, our system can assist the user at this time to provide more guarantee for safe driving. Furthermore, our system can also assist the driver to realize the emergency braking of the vehicle in advance. In the future, we intend to complete the above experiments in real vehicles and real driving scenes, and focus on improving the reliability of the system.

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