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Driving behavior recognition using EEG data from a simulated car-following experiment

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ABSTRACT

Driving behavior recognition is the foundation of driver assistance systems, with potential applications in automated driving systems. Most prevailing studies have used subjective questionnaire data and objective driving data to classify driving behaviors, while few studies have used physiological signals such as electroencephalography (EEG) to gather data. To bridge this gap, this paper proposes a two-layer learning method for driving behavior recognition using EEG data. A simulated car-following driving experiment was designed and conducted to simultaneously collect data on the driving behaviors and EEG data of drivers. The proposed learning method consists of two layers. In Layer I, two-dimensional driving behavior features representing driving style and stability were selected and extracted from raw driving behavior data using K-means and support vector machine recursive feature elimination. Five groups of driving behaviors were classified based on these two-dimensional driving behavior features. In Layer II, the classification results from Layer I were utilized as inputs to generate a k-Nearest-Neighbor classifier identifying driving behavior groups using EEG data. Using independent component analysis, a fast Fourier transformation, and linear discriminant analysis sequentially, the raw EEG signals were processed to extract two core EEG features. Classifier performance was enhanced using the adaptive synthetic sampling approach. A leave-one-subject-out cross validation was conducted. The results showed that the average classification accuracy for all tested traffic states was 69.5% and the highest accuracy reached 83.5%, suggesting a significant correlation between EEG patterns and car-following behavior.

1. Introduction

Driving behavior recognition is widely studied in the field of transportation to improve traffic efficiency and safety. As such, driving behavior recognition is a critical component in personalized driver assistance systems, where driving behavior types are categorized by the types of driving maneuvers and other performance measures. With proper categorization, unsafe driving behaviors can be better identified so that future driver assistance systems are able to alert drivers and neighboring vehicles. There is also the possibility of developing automated driving systems. For example, driving behavior recognition systems can detect and report the status of drivers to smart infrastructure and other manually driven or autonomous vehicles in a connected vehicle scenario. Such communication between vehicles and infrastructure would enhance the performance and reliability of transportation systems containing both manually driven and autonomous vehicles.

Typically, two types of data are available for driving behavior recognition: subjective questionnaire data and objective driving data. Driving behavior questionnaires (Reason et al., 1990) and driving skill inventories (Lajunen and Summala, 1995) are two common subjective evaluation methods utilized in driving behavior recognition. Zhang et al. (2009) proposed a quantitative method for analyzing driver characteristics based on driving behavior questionnaires. Traditionally, only one or two aspects of driving style have been considered in self-reported scales, such as aggressive or stressed driving styles. However, Taubman-Ben-Ari et al. (2004) constructed a multidimensional driving style inventory accounting for eight main aspects. Subsequently, Chung and Wong (2010) developed a five-aspect multidimensional driving style questionnaire. Martinussen et al. (2014) used both driving behavior questionnaires and driving skill inventories to identify different driver sub-groups.

Objective driving data (vehicle speed, acceleration, and position), collected from simulated or natural driving experiments, are the major

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sources of driving behavior recognition data. Bar et al. (2011) presented a probabilistic driving style determination method using fuzzy rules in various simulated traffic situations. Chen et al. (2013) proposed a driving behavior modeling system based on graph theory that constructs a driving habit graph. In natural driving experiments, in-vehicle sensors can provide the majority of the data utilized for driving action recognition, distraction detection, driver classification, and driving style recognition (Choi et al., 2007; Jensen et al., 2011; Van Ly et al., 2013). Recently, smartphones are being utilized as mobile sensors to recognize aggressive driving behavior (Johnson and Trivedi, 2011). GPS-based tracking devices can also help evaluate driver aggression (Constantinescu et al., 2010).

To compare the consistency of driving behavior classifications based on subjective evaluations and objective driving data, Wang et al. (2010) conducted a comparative driving behavior survey and a real-world driving experiment. The comparative results indicated that subjective evaluations are unreliable for parameterizing driver assistance systems.

Most existing studies assume that driving styles are fixed. Recently, Dorr et al. (2014) revealed that driving styles may vary with traffic conditions. Additionally, prevailing studies used either subjective evaluations or objective driving data, whereas only a few studies have used physiological data such as electroencephalography (EEG) to identify driving behavior. EEG has been recognized as an effective, non-invasive technique for monitoring and assisting real-world driving (Lin et al., 2005; Papadelis et al., 2007; Kar et al., 2010; Wang et al., 2015). In Chuang et al. (2015), EEG data were used to detect driving states, and warnings were provided to real-world drivers as feedback. Relative to traditional driving data, EEG shows two advantages in recognizing driving behavior: (1) EEG data have higher temporal resolution, allowing for real time EEG-based classifications; and (2) EEG data can provide extra information (physiological and emotional) in addition to kinematic vehicle indices.

In this study, six traffic flow conditions were designed in a simulated car-following experiment and a two-layer EEG-based driving behavior recognition system was proposed. The relationship between the car-following behavior and EEG measures was identified by constructing a classifier to recognize EEG patterns associated with car-following behaviors.

The objective of this study was to construct a driving behavior recognition system using EEG data and referencing the classification results of driving behavior data. The remainder of this paper is organized as follows: Section 2 introduces the experimental setup; Section 3 describes the methodology of the EEG-based driving behavior recognition system; Section 4 presents the classification results; and the discussion is presented in Section 5.

2. Experimental setup

2.1. Experimental apparatus

This experiment was conducted using the driving simulator at Beijing Jiaotong University (BJTU) (Li et al., 2016). The simulator consists of a full-size vehicle cabin with a real operating interface, an environmental noise and shaking simulation system, a vehicle dynamics simulation system, and a digital video replay system. It is a high-fidelity driving simulator with a linear motion platform ensuring one degree of freedom. The driving scenario is displayed on five screens around the vehicle with 300° surrounding vision.

A Neuroscan system was used to collect the EEG data, composed of a *SynAmps2*^{TM} amplifier and an electrode cap. There were 64 channels in the electrode cap, and their locations followed the international 10–20 system. The BJTU simulator and electrode cap are shown in Fig. 1

2.2. Participants

Fifty-two (52) healthy participants were recruited for this experiment. The average age of the participants was 35.21 years (S.D.[2] = 6.88). Their average driving experience was 9.64 years (S.D. = 6.55), and their average annual mileage was greater than 30,000 km. Before the experiment, each of them was required to complete a 10-min practice drive using the simulator, and none of the subjects showed simulator sickness.

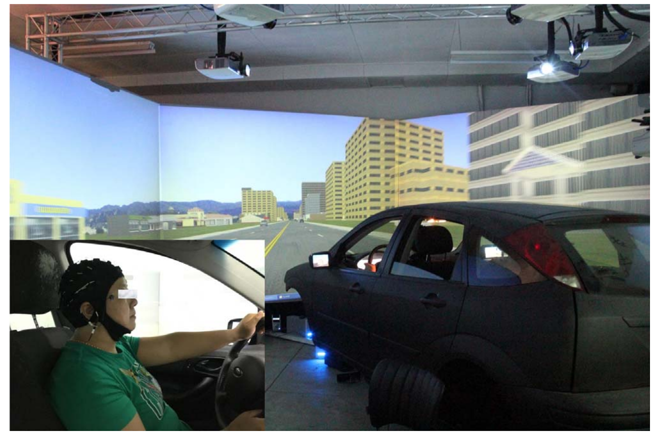

Fig. 1. BJTU driving simulator and electrode cap on driver.

2.3. Scenario design and experimental procedure

An eight-kilometer two-way straight road was designed as the driving scenario for this research. There were two lanes, each 3.75 m wide. The speed limit was 80 km/h and the road was surrounded by urban landscape.

The leading vehicle followed six travel patterns in this study, including four steady phases (free flow, coherent-moving flow, synchronized flow and jam (Guan and He, 2008)) and two complementary states (recovery from traffic jam and collision avoidance). To present these traffic states, six time periods were designed with specific accelerations and speed ranges for the leading vehicle (see Table 1). Fig. 2 shows the speed profile of the leading vehicle. To mimic a real-world driving environment, an additional vehicle was displayed 30 m ahead of the leading vehicle and random traffic was displayed on the opposite lane.

During the experiment, all participants were asked to drive according to their daily driving habits while obeying traffic rules. There was only one lane for the test vehicle to travel, and participants were not permitted to overtake the leading vehicle. The car-following process lasted 615 s. According to the speed profile of the leading vehicle, the car-following process was divided into six driving periods and the driving behavior recognition for each period was studied subsequently. Driving simulator and EEG data were collected simultaneously during the experiment.

2.4. Driving measures

2.4.1. Driving data acquisition

Driving data were collected from the driving simulator with a sampling rate of 60 Hz. Fourteen (14) key variables (see Table 2) were selected for further analyses, reflecting both longitudinal and lateral vehicle movements such as longitudinal acceleration and lateral lane deviation. Additionally, the relationship between the following and leading vehicles was evaluated using space headway, time headway, and relative speed.

[2] S.D. is the standard deviation.