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Identification of common features of vehicle motion under drowsy/distracted driving: A case study in Wuhan, China

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ABSTRACT

Drowsy/distracted driving has become one of the leading causes of traffic crash. Only certain particular drowsy/distracted driving behaviors have been studied by previous studies, which are mainly based on dedicated sensor devices such as bio and visual sensors. The objective of this study is to extract the common features for identifying drowsy/distracted driving through a set of common vehicle motion parameters. An intelligent vehicle was used to collect vehicle motion parameters. Fifty licensed drivers (37 males and 13 females, $M = 32.5$ years, $SD = 6.2$) were recruited to carry out road experiments in Wuhan, China and collecting vehicle motion data under four driving scenarios including talking, watching roadside, drinking and under the influence of drowsiness. For the first scenario, the drivers were exposed to a set of questions and asked to repeat a few sentences that had been proved valid in inducing driving distraction. Watching roadside, drinking and driving under drowsiness were assessed by an observer and self-reporting from the drivers. The common features of vehicle motions under four types of drowsy/distracted driving were analyzed using descriptive statistics and then Wilcoxon rank sum test. The results indicated that there was a significant difference of lateral acceleration rates and yaw rate acceleration between "normal driving" and drowsy/distracted driving. Study results also shown that, under drowsy/distracted driving, the lateral acceleration rates and yaw rate acceleration were significantly larger from the normal driving. The lateral acceleration rates were shown to suddenly increase or decrease by more than $2.0\,m/s^3$ and the yaw rate acceleration by more than $2.5°/s^2$. The standard deviation of acceleration rate (SDA) and standard deviation of yaw rate acceleration (SDY) were identified to as the common features of vehicle motion for distinguishing the drowsy/distracted driving from the normal driving. In order to identify a time window for effectively extracting the two common features, a double-window method was used and the optimized "Parent Window" and "Child Window" were found to be 55 s and 6 s, respectively. The study results can be used to develop a driving assistant system, which can warn drivers when any one of the four types of drowsy/distracted driving is detected.

1. Introduction

Drowsy/distracted driving has been shown to have a significant impact on traffic safety (Connor et al., 2002; Thiffault and Bergeron, 2003; Wilson and Stimpson, 2010; Hallvig et al., 2013). Drowsy/distracted driving is defined as, while operating a motor vehicle, driver is affected by distraction, drowsiness, drinking, talking on the phone or to a passenger, texting, eating, or reading etc. The 100-Car Naturalistic Driving Study found that almost 80% of all crashes and 65% of all near-crashes involved drowsy driving (Dingus et al., 2006). The U.S. National Highway Traffic Safety Administration has identified drowsy/distracted driving as a high priority area to improve traffic safety (Stutts et al., 2003).

In order to prevent the traffic accidents resulting from drowsy/distracted driving, it is critical to develop an effective method for detecting such driving state. The common practice of detecting drowsy/distracted driving is to analyze the differences between drowsy/distracted driving and the "normal" driving. The following paragraphs provide a brief review to related studies for detecting drowsy and distracted driving, with the first half for the former and the second half for the latter.

In recent years, many studies (Verwey and Zaidel, 2000; Friedrichs and Yang, 2010; He et al., 2011; Yan et al., 2013) have

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been conducted to analyze drowsy driving. Three approaches were widely used including physiological, behavioral and vehicle-based.

Physiological signals, such as heart rate variability (HRV), have been widely used for the detection of drowsy driving. For example, Li and Chung (2013) collected the HRV and classified them for both the alert and the drowsy driving scenario with the wavelet transform method. Patel et al. (2011) used the different frequencies of HRV between normal driving and drowsy driving to detect drowsy driving. In a study by Hu and Zheng (2009), the eyelid movement data was collected and the three classes of drowsiness were developed. The eyelid parameters were identified by a paired *t*-test to detect the drowsy driving. As another example, Lin et al. (2005) collected the electroencephalogram (EEG) signals through driving simulators for detecting the drowsy driving. Akin et al. (2008) developed a new method using a combination of EEG and EMG signals to detect drowsiness. The accuracy of detection was about 98–99%.

Similarly, behavioral characteristics, such as eye closure rate, nodding head and eye blinking, have been collected and analyzed for detecting drowsy driving. For example, eye closure frequency under alert and drowsiness were studied by Hayami et al. (2002). It is found that the high eye closure frequency indicates a drowsy driving state. Hamada et al. (2003) used the blink frequencies to judge drivers' drowsiness state. They found that the long eyelid closure time increased when the drivers are in a drowsiness state. As another example, Hong et al. (2007) used the horizontal projection of the face and geometrical position of eye for detecting the drowsiness and a set of dynamic thresholds was established to judge if the drowsy driving was presented. Similarly, in another study by Vural et al. (2007), the inner brow rise, lip stretch and outer brow rise were used to detect drowsy driving.

Another method to analyze drowsy driving is vehicle-based measurement. For example, the steering wheel movement and standard deviation of lane position (SDLP) has been used for a detection of drowsy driving (Thiffault and Bergeron, 2003; Ting et al., 2008). As another example, Ingre et al. (2006) found that the SDLP increased when the drivers are in a drowsiness state. Wang (2012) attached a transformer angular displacement sensor, a GPS device and embedded system onto the steering wheel. The corner voltage changes of steering wheel were collected using transformer angular displacement sensor and the speed of vehicle was recorded the GPS device. The combined data from the two sources were used to detect drowsy driving.

In order to detect the distracted driving, the vision of driver has been collected and analyzed. For example, Zeng et al. (2010) monitored the states of drivers' eyes and heads. Driver's gaze was estimated using head motion and eye states to detect distracted driving. As another example, Liang et al. (2007) collected driver's eye movements and driving performance data through driving simulators to detect distracted driving. Miyaji et al. (2009) designed a topic conversation experiment and carried it out on a driving simulator to study the distracted driving. The driver's eyes and head movements were tracked with stereo camera system. The distracted driving was detected with a detection algorithm – AdaBoost.

In addition, the cognitive process of drivers was analyzed to detect the distracted driving. For examples, Liang and Lee (2010) found that cognitive distraction resulted in a less smooth operation of the steering wheel (under-compensation and over-compensation). Brain activity (EEG alpha spindles) and the reaction time to the braking were used by Sonnleitner et al. (2014). They found that the reaction time and alpha spindle rate under cognitive distraction were higher than normal driving. As another example, Ishida and Matsuura (2001) collected the braking response time, eye movement, headway and lane departure in a simulated experiment. They found that the braking response time and the headway increased under distracted driving. Similarly, in another study by Patten et al. (2004), different types of conversations and picking up/return phone calls were used to induce distracting. They found that the reaction time for operating vehicle significantly increased under distracted driving.

The literature review for this study indicates that most of previous studies focus on one particular type of drowsy/distracted driving and common features for detecting/identifying different types of drowsy/distracted driving cannot be generalized. Most of the detection methods used in the previous studies use biosensors, and therefore require attaching sensors onto driver's body. In addition, most of the experiments in the previous studies were carried out based on driving simulators. Although these methods have benefited the understanding of drowsy/distracted driving behaviors, significant differences between simulated and field driving could well skew some of important findings. In addition, collecting motion parameters is much easier than obtaining the driver behavior and physiology feature data, as the former does not require attaching any sensors onto the driver and therefore the experiments are much realistic to the test drivers and easier to operate. Therefore, the purpose of this paper is to find a set of common features of vehicle motion under different types of drowsy/distracted driving based on a field study in Wuhan, China.

In this study, on-road experiments were conducted to collect vehicle motion parameters, including lateral acceleration, yaw rate, longitudinal acceleration and orientation angle, by an inertial navigation system. Vehicle motion data from the field studies under the following four scenarios: talking, watching roadside,

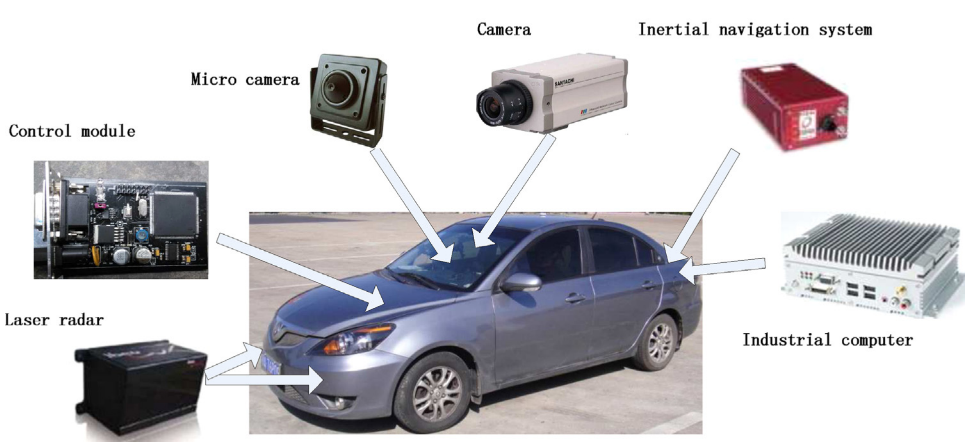

Fig. 1. The test vehicle.

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