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Real-time detection of drivers' texting and eating behavior based on vehicle dynamics

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ABSTRACT

With rapid advancement in cellphones and intelligent in-vehicle technologies along with driver's inclination to multitasking, crashes due to distracted driving had become a growing safety concern in our road network. Some previous studies attempted to detect distracted driving behaviors in real-time to mitigate their adverse consequences. However, these studies mainly focused on detecting either visual or cognitive distractions only, while most of the real-life distracting tasks involve driver's visual, cognitive, and physical workload, simultaneously. Additionally, previous studies frequently used eye, head, or face tracking data, although current vehicles are not commonly equipped with technologies to acquire such data. Also those data are comparatively difficult to acquire in real-time during traffic monitoring operations. To address the above issues, this study focused on developing algorithms for detecting distraction tasks that involve simultaneous visual, cognitive, and physical workload using only vehicle dynamics data. Specifically, algorithms were developed to detect driving behaviors under two distraction tasks – texting and eating. Experiment was designed to include the two distracted driving scenarios and a control with multiple runs for each. A medium fidelity driving simulator was used for acquiring vehicle dynamics data for each scenario and each run. Several data mining techniques were explored in this study to investigate their performance in detecting distraction. Among them, the performance of two linear (linear discriminant analysis and logistic regression) and two nonlinear models (support vector machines and random forests) is reported in this article. Random forests algorithms had the best performance, which detected texting and eating distraction with an accuracy of 85.38% and 81.26%, respectively. This study may provide useful guidance to successful development and implementation of distracted driver detection algorithms in connected vehicle environment, as well as to auto manufacturers interested in integrating distraction detection systems in their vehicles.

1. Introduction

Engineers and researchers in transportation and automotive engineering are continuously working on improving the safety of roadway and automobile users. Consequently, recent roadways and vehicles have been equipped with many new safety features, which resulted in a 29% decrease in fatality rate per 100 million vehicle miles travelled between

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2000 and 2013 (FARS, 2016). Although, this decrease may indicate that our roadways are becoming safer day-by-day, crashes resulting from driver distraction are experiencing a growing trend. Results from the 100-car naturalistic study reported that distraction contributed to 43% of crashes and 27% of near crashes (Klauer, Neale, Dingus, Ramsey, & Sudweeks, 2005), which clearly indicates driver distraction is an important safety concern in our transportation network; and therefore, distraction detection and mitigation will result in significant social and economic benefits.

Driver distraction can be defined as "*diversion of attention away from activities critical for safe driving toward a competing activity*" (Lee, Young, & Regan, 2008). It can deteriorate driving performance visually (not looking at the road), cognitively (not paying attention to the road), and physically (hands off the steering wheel) (Chaudhary, Casanova-Powell, Cosgrove, Reagan, & Williams, 2014). Distracted driving has been acknowledged to negatively affect driver performance and increase the risks of associated crashes and near-misses (Amditis, Pagle, Joshi, & Bekiaris, 2010). The affected driver performance includes reduced lateral and longitudinal control, reduced situational awareness, and slower response times, with effects being more pronounced for older drivers (Engetorm, Johansson, & Ostlund, 2005; Rakauskas, Gugerty, & Ward, 2004; Kass, Cole, & Stanny, 2007; Ranney, 2005).

Previous studies suggested that cell phone use is one of the most common distracting activities drivers are likely to engage (NHTSA, 2011). A survey, conducted by American Automobile Association in 2008, reported that 14.1% of all drivers and 48.5% of young drivers (18–24 years) admitted of being involved in texting while driving (AAA, 2008). Besides cell phone use, eating is another common distracting activity. A survey on 2800 U.S. adults reported that 86% of the drivers were involved in eating while driving at least once in past one month (Gardner, 2011).

Developing distracted driver detection algorithms implementable to traffic monitoring operations and adaptive in-vehicle systems capable of assisting drivers to diminish distraction could be promising strategies to improve traffic safety. To implement such strategies, accurate detection of distracted driving behaviors in real-time is critical. However, the focus of distracted driving studies has been on the impact of distraction activities on driver performance. Only a few efforts were made to identify distracted drivers, and most of these studies used non-vehicle system data such as eye, face, or head tracking features (Liang, Reyes, & Lee, 2007; Wöllmer et al., 2011; Jo, Jung, Park, & Kim, 2011; Sigari, Fathy, & Soryani, 2013; Liang & Lee, 2014). Those data are comparatively difficult to acquire in real-time during traffic monitoring operations. Additional in-vehicle data collection devices are required to gather these data, which are not commonly installed in regular vehicles. As a result, the need for a distracted driver detection algorithm that is implementable to real-time traffic monitoring operations remains unmet. In response to this need, the objective of the research herein was to explore statistical data mining approaches to develop algorithms to detect distracted and non-distracted drivers using only vehicle dynamics related data collected from driving simulator experiments.

Additionally, the previous studies mainly focused on detecting either visual (Kircher & Ahlstrom, 2010; Tango & Botta, 2013) or cognitive (Liang et al., 2007; Liang & Lee, 2014; Jin et al., 2012) distraction. Few efforts have been taken to detect combined visual and cognitive distraction. However, real-life distracting tasks often increase drivers' visual, cognitive, and physical workload, simultaneously (e.g., texting while driving simultaneously cause visual, cognitive, and physical distraction). Therefore, there is a necessity to develop detection algorithms capable of capturing combined effects of visual, cognitive, and physical workload on drivers' performance. However, detecting visual, cognitive, and physical distraction separately and integrating them together into a single detection algorithm could be complicated. Task specific detection algorithms (i.e., algorithms to detect texting/eating) may provide a realistic solution to this complicated issue. Thus, this study attempted to develop real-time detection algorithms for two specific tasks, namely texting and eating.

Another common trend among many of the previous studies is that the detection algorithms were trained and validated for individual participants commonly known as intra-subject approach (Liang et al. 2007; Ersal, Fuller, Tsimhoni, Stein, & Fathy, 2010; Tango & Botta, 2013; Liang & Lee, 2014; Jin et al., 2012). To justify their approach, researchers claimed that distraction affects different drivers in different magnitudes; therefore, distraction detection algorithms should be customized to individual participants. While their claim is true, intra-subject distraction detection algorithms may not be implementable to traffic monitoring operations, as these algorithms are specific for individual drivers. Thus, this study attempted to develop algorithms to detect distractions adopting "inter-subject" approach, which will likely make it easier to implement in the traffic monitoring operations.

2. Literature review

Over the past decade, numerous researchers attempted to develop algorithms to detect driver distraction. These studies vary in a number of aspects. Some used driving simulators to obtain data, other used test track and/or naturalistic driving. The number of subjects employed in these studies also varied widely. Moreover, these studies also vary in their primary objectives of detecting specific type/types of distraction (i.e., visual, cognitive or combined). Table 1 presents a list of key studies relevant to distracted driving detection to date.

Zhang, Owechko, Zhang, and Washington (2004) performed one of the earliest studies to detect driver's cognitive distraction. They used decision tree classifier to identify distracted and non-distracted states based on the driving performance and eye-gaze related features. Liang et al. (2007) investigated real-time cognitive distraction detection using Support Vector Machines (SVM). Driving performance and eye tracking features obtained from a driving simulator study involving six male and four female participants were used as the input variables to develop SVM algorithms. Distraction detection models was