Estimation of Cognitive Distraction from Driver Gazing

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ABSTRACT

In their study, the authors sought to generate rules for cognitive distractions of car drivers using data from a driving simulation environment. They collected drivers’ eye-movement and driving data from 18 research participants using a simulator. Each driver drove the same 15-minute course two times. The first drive was normal driving (no-load driving), and the second drive was driving with a mental arithmetic task (load driving), which the authors defined as cognitive-distraction driving. To generate rules of distraction driving using a machine-learning tool, they transformed the data at constant time intervals to generate qualitative data for learning. Finally, the authors generated rules using a Support Vector Machine (SVM).

KEYWORDS

1. INTRODUCTION

In recent years, investigators have focused on detecting risks of car driving by analyzing driving and drivers’ data to realize safe driving (Yoshizawa & Iwasaki, 2015). To predict driver’s act is important to prevent accidents. And it needs to know how human brain works. So, researchers have been trying to understand cognitive mechanisms from various points of view, including relation between attention and gazing. (Wang et al., 2013; Engelke, Duenser, & Zeater, 2014) We have improved on studies that recognize the mental model in driving (Sega, Iwasaki, Hiraishi, & Mizoguchi, 2011) and detect stress states (Mizoguchi, Ohwada, Nishiyama, & Iwasaki, 2013). Recently, we have focused on detecting cognitive distraction in car driving.
The National Highway Traffic Safety Administration (NHTSA) has identified three types of driving distractions (NHTSA, 2010): (1) visual, (2) cognitive, and (3) manual. Visual distraction occurs while viewing an unrelated object (i.e., look-away driving). Viewing and operating a smartphone, viewing the car’s TV, and operating and viewing the car navigation system are visual distractions. The visibility of outside material (beyond safety checks) during driving is also a visual distraction.

Cognitive distraction involves the internal state of a driver who is thinking about unrelated things while driving. Examples include driving while talking on a cell phone and concentrating on one’s thoughts. Manual distraction involves an intentionally careless driver. To detect visually distracted driving, we measure the driver’s eye movements. However, cognitive distraction involves the driver’s internal state, so it is difficult to detect cognitive distraction using just eye movement and driving data (Sega, Iwasaki, Hiraishi, & Mizoguchi, 2011).

To improve detection, we researched cognitive distraction states based on eye-movement data using neural networks (Harada, Iwasaki, Mori, Yoshizawa, & Mizoguchi, 2014). In this research, we created an evaluation model of a cognitive distraction state, but we could not adapt the model to car driving data.

In our study, we generated rules to determine whether or not a driver is cognitively distracted, using data regarding the driver’s eye movement and driving data collected using a Support Vector Machine (SVM) (Vapnik, 1995). To generate these rules, we assigned a mental arithmetic task to the research participants to cause cognitive distraction (e.g., Harbluk’s method) (Harbluka, Noyb, Trbovicha, & Eizenmanc, 2007). In addition, we used simulation to ensure safety (Figure 1). We gathered two types of data: normal driving and driving with a mental arithmetic task as a cognitive distraction. We then determined the rules of cognitive distraction using the cognitively

Figure 1. Simulator environment photographed using the camera of the eye-movement measuring device EMR
Decision Support System for Greenhouse Tomato Yield Prediction using Artificial Intelligence Techniques
www.igi-global.com/chapter/decision-support-system-greenhouse-tomato/56210?camid=4v1a

Optimization of a Hybrid Methodology (CRISP-DM)
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