Accident Analysis and Prevention 99 (2017) 321–329

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Predicting drowsy driving in real-time situations: Using an advanced driving simulator, accelerated failure time model, and virtual location-based services

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ARTICLE INFO

Article history:
Received 17 July 2016
Received in revised form
24 November 2016
Accepted 20 December 2016

Keywords:
Drowsy driving
Duration prediction
Accelerate failure time
Location based service
Drowsy driving warning system

ABSTRACT

This paper aims to both identify the factors affecting driver drowsiness and to develop a real-time drowsy driving probability model based on virtual Location-Based Services (LBS) data obtained using a driving simulator. A driving simulation experiment was designed and conducted using 32 participant drivers. Collected data included the continuous driving time before detection of drowsiness and virtual LBS data related to temperature, time of day, lane width, average travel speed, driving time in heavy traffic, and driving time on different roadway types. Demographic information, such as nap habit, age, gender, and driving experience was also collected through questionnaires distributed to the participants. An Accelerated Failure Time (AFT) model was developed to estimate the driving time before detection of drowsiness. The results of the AFT model showed driving time before drowsiness was longer during the day than at night, and was longer at lower temperatures. Additionally, drivers who identified as having a nap habit were more vulnerable to drowsiness. Generally, higher average travel speeds were correlated to a higher risk of drowsy driving, as were longer periods of low-speed driving in traffic jam conditions. Considering different road types, drivers felt drowsy more quickly on freeways compared to other facilities. The proposed model provides a better understanding of how driver drowsiness is influenced by different environmental and demographic factors. The model can be used to provide real-time data for the LBS-based drowsy driving warning system, improving past methods based only on a fixed driving.

1. Introduction

Drowsy driving is a common threat that endangers the lives of drivers and nearby road users alike. Studies have repeatedly shown that drowsy driving plays a critical role in traffic collisions, disproportionately affecting severe and fatal crashes (Pack et al., 1995; Maycock 1996; Lyznicki et al., 1998; Williamson et al., 2001; Vanlaar et al., 2008; Accidentes 2015; Zhang et al., 2016). Despite this evidence, drivers continue this risky behavior and the number of collisions and fatalities caused by drowsy driving have remained high throughout the past decades. Horne and Reyner (1995) found that 23% of accidents occurring on monotonous motorways were related to drowsy driving. Using a multiple imputation methodology, Tefft (2014) estimated that drowsy driving accounted for 7% of all crashes and 16.5% of fatal crashes in the US from 2009 to 2013. Furthermore, a nationally representative telephone survey in the US found that 41% of drivers admit to having “fallen asleep or nodded off” while driving (Suite 2010). Smith et al. (2005) conducted a 4-week follow-up study finding that young adult drivers felt drowsy while driving in more than 23% of the cases.

Drowsy driving may be caused by limited sleep, long periods of driving, and monotonous environments, among other possibilities (Saccomanno et al., 1970; Arnold and Hartley 1998; Hu et al., 2010). Several countermeasures have been adopted in an attempt to mitigate these causes. In some cases, collisions related to drowsy driving can be avoided by alerting drivers to their potential drowsiness, allowing them to take a break from driving before an incident occurs (Kulmala 1997; Ferdinands 1999; Regan et al., 2001; Young et al., 2003). Maximum continuous driving times have been proposed to allow drivers to take breaks during their trip. Drowsy driving warning systems relying on facial recognition techniques have been developed and used to warn drivers who are falling asleep (Grace and Steward 2001). Meanwhile, warning signs and

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http://dx.doi.org/10.1016/j.aap.2016.12.014
0001-4575/

indicators of drowsy driving have been installed in monotonous environments to alert drivers to the possibility of drowsiness. However, such systems may be difficult to implement in practice, as drowsy driving is a gradual behavior which occurs without the drivers' knowledge. Modeling the drowsy driving time, the time spent driving before signs of drowsiness are detected, and understanding the impact of different factors on drowsy driving time will help to understand how built environment and personal habits are related to the probability of drowsy driving. Additionally, facial recognition warning systems can be developed according to the probability of drowsiness, to either better alert drivers to take breaks before dangerous levels of drowsiness set in, or when to stop driving if dangerous levels of drowsiness are reached.

Driving data is difficult to obtain in real-world traffic environments because of the potential danger to participants. This is especially true of drowsy driving studies which require participants to be drowsy in order to collect meaningful data. Selecting proper testing environments may be difficult, as continually changing road environments make it is impossible to isolate specific built environment variables. Therefore, driving simulation experiments are preferred and should be expected. However, because of the challenges in simulating experiences which closely mirror real-world expectations, the reliability of driving simulators in studying drowsy driving behavior has been challenged. Nevertheless, researchers at universities and other institutions have invested time and money in developing and building advanced driving simulators which provide experiences much closer to what would be expected in the field (Slob 2008; Fischer et al., 2010; Lin et al., 2015). With these advanced simulators, drowsing driving in real-world scenarios can be better explored. In this study, a driving simulator was used to collect virtual Location Based Service (LBS), services provided by applications that offer geographic location data and provide rich information of the built environment including geometric road data. This virtual LBS data, including drowsy driving time and other driving information, can be easily collected in the field using LBS devices.

The objective of this study is to build a real-time drowsy driving probability model for predicting continuous driving time before the onset of driver drowsiness, considering different factors such as driver gender, age, experience, and sleeping habits, weather condition and temperature, road type, time of day, and traffic condition. For this purpose, an Accelerated Failure Time (AFT) model was developed based on 258 experimental drowsiness records collected from an advanced driving simulator with 8° of freedom. This model could be used as the basis for a drowsy warning system based on LBS.

2. Literature review

The key task explored in past research of drowsy driving warning systems is the detection and recognition of drowsiness. Based on past literature, approaches in identifying drowsy driving can be classified into two categories: (a) identifying drowsy driving by setting a fixed driving time threshold, with which drowsy driving would be identified if the continuous driving time exceeds such threshold; (b) detecting and identifying drowsy driving through multiple aspects of the driver or the vehicle in addition to the driving time factor, such as cognitive distraction, physiological reaction, facial expression, or vehicle operation condition. Eriksson and Papanikolopoulos (2001) recognized drowsy driving based on the analysis of facial expressions including eye blink times, eye closure duration, and eyelid movement. Yeo et al. (2009) developed a method of Automatic Electroencephalographic (EEG) for detecting drowsiness with the application of a Support Vector Machine (SVM). Wang et al. (2015) also proposed an EEG-based detection method to determine driving drowsiness in real-time by analyzing drivers' neural mechanisms. Such methods, though gaining their attention due to the awareness of the hazards of drowsy driving, have still not been widely utilized and remained to be improved. Considering driving time, as one of the key factors associated to drowsy driving, modeling driving time and use a calibrated driving time threshold from the model potentially helps increase the performance of drowsiness detection. In practice, traditional drowsy driving warning systems based on time spent driving adopt a simple fixed driving time as the upper threshold for alerting drivers. Such thresholds have been investigated in several studies. For example, Yanli et al. (2009) used psychological tests and subjective drowsiness investigation, concluding that continuous driving time should not exceed 3.5 h. Other studies have detected drowsy driving through driver behavior. In one example, Mcdonald et al. (2013) identified drowsy driving based lane departure degree and steering wheel angle.

Several studies have investigated the relationship between driving duration or distance, factors of the built environment or driver, and drowsiness. Friswell and Williamson (2013) studied the impacts of vehicle type and driving distance and duration on drowsiness and found that, on average, drivers of short haul light vehicles felt drowsy after 6 h of driving, while drivers of long distance heavy vehicles felt drowsy after 11 h. Sang and Li (2012) tested the psychological fatigue of bus drivers using a Psychology Fatigue Measurement System. The authors found that drivers' operation capability decreased after 4 h of continuous driving due to drowsiness. Many studies investigated the impact of driving environment on drowsy driving. Pilcher and Huffcutt (1996) identified that complex road environments and traffic conditions made drivers more vulnerable to the effects of drowsiness. However, a study conducted by Liu and Wu (2009) illustrated that complex driving environments did not necessarily increase the likelihood of drowsiness compared to monotonous environment. In their study, both environments induced drowsy symptoms after 60 min of driving. Others have explored the impact of driver working time on their sleep conditions (Jones et al., 2005). Despite the progress made in this past research, these studies fall short to some extent, as drowsy driving is explained by a combination of different factors from the built environment and individual driver. Modeling the impact of these factors on drowsy driving, specifically on the duration/distance of continuous driving before detection of drowsiness, should be considered.

In the past several decades, different methods have been investigated for modeling driving duration. Such models include models based on variance analysis, regression, non-parametric regression, hazard-based methods, decision tree, fuzzy logic, Artificial Neural Network and Bayesian Networks. Among these models, hazard-based duration models have recently gained popularity. Hazard-based duration models study the conditional probability of an event ending given that the event has lasted up until a specified time (Washington et al., 2010). As the time variable is connected with a conditional probability, hazard-based duration modeling allows for the explicit study of the relationship between drowsy driving duration and the explanatory variables. Accelerated Failure Time (AFT) models are effective and easily interpretable parametric approaches that can incorporate the effect of external covariates on the hazard function (Greene 2003), improving prediction for cases with missing data. As a result, the AFT model has been applied extensively in a number of transportation fields such including incident duration (Junhua et al., 2013) and pedestrian waiting duration (Yang et al., 2015).

Driver warning systems with fixed driving durations can be improved with a dynamic driving duration threshold dependent on different driver and built environment factors. LBS are a good source for built environment data, and can provide the necessary environ-