Accident Analysis and Prevention 113 (2018) 25–37

Contents lists available at ScienceDirect

Accident Analysis and Prevention

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

A contextual and temporal algorithm for driver drowsiness detection

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ARTICLE INFO

Keywords:
Drowsiness
Detection
Dynamic Bayesian Network
Random forest
Driver safety

ABSTRACT

This study designs and evaluates a contextual and temporal algorithm for detecting drowsiness-related lane. The algorithm uses steering angle, pedal input, vehicle speed and acceleration as input. Speed and acceleration are used to develop a real-time measure of driving context. These measures are integrated with a Dynamic Bayesian Network that considers the time dependencies in transitions between drowsiness and awake states. The Dynamic Bayesian Network algorithm is validated with data collected from 72 participants driving the National Advanced Driving Simulator. The algorithm has a significantly lower false positive rate than PERCLOS—the current gold standard—and baseline, non-contextual, algorithms under design parameters that prioritize drowsiness detection. Under these parameters, the algorithm reduces false positive rate in highway and rural environments, which are typically problematic for vehicle-based detection algorithms. This algorithm is a promising new approach to driver impairment detection and suggests contextual factors should be considered in subsequent algorithm development processes. It may be combined with comprehensive mitigation methods to improve driving safety.

1. Introduction

The National Highway Traffic Safety Administration (NHTSA, 2011) reported drowsiness contributes to approximately 83,000 crashes, 37,000 injuries, and 900 deaths each year—accounting for approximately 3% of all traffic-related fatalities. The 100-Car naturalistic driving study found that drowsy driving contributed to 22%–24% of the crashes and near-crashes observed (Klauer et al., 2006). Crash survey data illustrate that this problem is not unique to American drivers—-drowsiness contributes to as many as 7% of crashes in the United Kingdom and 3.9% of crashes in Norway (Maycock, 1997; Sagberg, 1999). The variance in these estimates reflects the difficulty associated with identifying drowsiness-related crashes. This difficulty is driven by the fact that drowsiness leaves no physical trace and is a subjective experience. This lack of physical evidence suggests that the crash statistics and surveys may underestimate the true problem of drowsy driving.

The majority of drowsiness-related crashes, nearly 80%, can be classified as single car run off road crashes, where the driver stops controlling their vehicle and eventually departs their lane and the roadway (Pack et al., 1995). Reducing these crashes requires a multi-faceted approach including schedule restrictions for professional drivers (Gander et al., 2011), increased education for drivers (Fletcher et al., 2005), laws against drowsy driving (Geist et al., 2002), driver feedback (Aidman et al., 2015), and detection and mitigation technology (Balkin et al., 2011). The role of detection and mitigation technology in this approach is to provide an intervention immediately prior to a crash that prevents the crash from occurring or reduces its severity. One specific goal of detection and mitigation technology is to detect and prevent single car run off road crashes caused by drowsiness. The scope of this goal includes both cases of prolonged and intermittent drowsiness.

Detection and mitigation technology consists of collecting data from the driver, vehicle, or environment, applying a classification algorithm to these data, and presenting the result of the classification algorithm to the driver (Balkin et al., 2011). A substantial amount of research has been dedicated to optimizing the data collection and classification algorithm application (Liu et al., 2009). The goals of this research typically center on introducing novel input measures (Dinges and Grace, 1998; Lal et al., 2003), evaluating the use of machine learning approaches that have been successful in other domains (Patel et al., 2011; Yang et al., 2010; Yeo et al., 2009), or introducing novel pre-processing steps to improve classification (Kutila et al., 2007; Sayed and Eskandarian, 2001). These three directions of research can be condensed into a discussion of algorithm input and machine learning methods.

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https://doi.org/10.1016/j.aap.2018.01.005
Received 20 September 2016; Received in revised form 5 January 2018; Accepted 6 January 2018
0001-4575/ Published by Elsevier Ltd.

1.1. Drowsiness detection algorithm input

Drowsiness detection algorithm input sources can be differentiated by the raw measurement and the processing steps taken to convert measurements into features. Measures explored in the literature include: heart rate (Furman et al., 2008), brain activity (Dinges et al., 1998; Lal et al., 2003), eye closure and tracking (Dinges et al., 1998; Ji et al., 2004; Wierwille et al., 1994b), lane position (Hanowski et al., 2008a), and steering-wheel angle (Eskandarian and Mortazavi, 2007; Krajewski, Golz, et al., 2009; Krajewski and Sommer, 2009; Sayed and Eskandarian, 2001). Although most previous algorithms focus on a one type of measure, several employ a combination of measures (Forsman et al., 2013; Hanowski et al., 2008b; Ji et al., 2004; Tijerina et al., 1999; Zilberg et al., 2007). The most commonly applied and theoretically rigorous measures are electroencephalogram (EEG), percent eye-closure over a fixed time window (PERCLOS), and steering-wheel angle (Balkin et al., 2011). EEG is advantageous because spectral patterns in the signal have a well-established link to the transition between wakefulness and sleep (Lal and Craig, 2001). EEG is limited by the amount of pre-processing required prior to classification, vulnerability to artifacts, and the feasibility of collecting EEG from drivers in real situations. PERCLOS, developed by Wierwille et al. (1994a), is the gold standard measure for drowsiness detection. PERCLOS predicts drowsiness based on the percentage of time an individual's eyes are more than 80% closed over a 2-min period. Dinges et al. (1998) demonstrated that the PERCLOS algorithm had over 90% accuracy in detecting degraded performance during a vigilance task, which was more reliable across drivers than EEG, blinks, and head position in the study. PERCLOS has been incorporated into aftermarket devices such as the Co-pilot (Grace and Stewart, 2001) and has been used as a ground truth measure of drowsiness (Tijerina et al., 1999; Wierwille et al., 1994b). Despite its wide acceptance PERCLOS has several practical limitations. PERCLOS for real-time detection is limited because current camera technology required for its measurement is expensive, has not been extensively validated, and may be unreliable when the driver wears sunglasses or under weather conditions that produce high amounts of glare (Balkin et al., 2011). Despite these limitations, the substantial evidence showing the utility of PERCLOS suggests that it might be useful for benchmarking new algorithms.

The limits of PERCLOS and EEG have led researchers to examine steering-wheel angle, or the deflection of the top of the wheel from the zero point. Steering-wheel angle is similar to EEG data in that it requires significant pre-processing and transformation before it becomes a viable input measure. Sayed and Eskandarian (2001) introduced a steering-wheel angle based algorithm that filtered raw steering angle measure to remove road curvature events, and then discretized into bins of steering patterns. The algorithm classified drivers labeled as sleep deprived or non-sleep deprived with nearly 90% accuracy. Similarly, Krajewski et al. (2009) developed an algorithm that processed raw steering-wheel angle data into features characterized the signal in the time and frequency domains. The algorithm also included features representing the non-linear aspects of steering-wheel angle patterns. The algorithm achieved 86% accuracy in identifying self-reported sleepiness. McDonald et al. (2013a) presented an approach that used raw steering-wheel angle data, however the machine learning technique applied internally filtered the data. The algorithm performed comparably to PERCLOS in detecting drowsy-related lane departures. Steering-wheel data is limited in two primary facets. First, it is highly sensitive to differences in driving activities, such as curve negotiation, and thus detection could be confounded with differences in the driving context (Balkin et al., 2011; Hartley et al., 2000). Second, patterns in steering wheel angle that are indicative of drowsiness, namely a lack of steering input, are often also associated with other impairments such as distraction. To overcome these limitations, steering-wheel angle based algorithms accommodate road artifacts and either carefully consider the ground truth definition of drowsiness or be trained to differentiate multiple types of impairment. Algorithms that focus solely on drowsiness detection using steering wheel angle must have a ground truth definition that clearly differentiates between distraction and drowsiness.

1.2. Machine learning methods in drowsiness detection algorithms

Machine learning methods can be characterized by their training procedure, prediction procedure, and their optimization parameters (Kotsiantis et al., 2007). The drowsiness detection literature has explored a variety of methods including: Decision Trees (Krajewski and Sommer, 2009; McDonald et al., 2013b), Neural Networks (Eskandarian and Mortazavi, 2007; Garcés Correa et al., 2014; Patel et al., 2011; Sandberg et al., 2011; Sayed and Eskandarian, 2001; Vuckovic et al., 2002; Wilson and Bracewell, 2000), Support Vector Machines (Awais et al., 2017; Hu and Zheng, 2009; Jo et al., 2014; Kutila et al., 2007; Lee et al., 2015; Sun et al., 2017; Zhao et al., 2012), Logistic Regression (Murata, 2016), Random Forests (McDonald et al., 2013b; Wang et al., 2016), Bayesian Networks (Ji et al., 2004; Yang et al., 2009), and Dynamic Bayesian Networks (Ji et al., 2006; Yang et al., 2010; Yang et al., 2009). Of these approaches Dynamic Bayesian Networks (DBN) are the most promising for future work because they explicitly model the time-dependent nature of driver drowsiness and allow the inclusion of contextual factors that influence drowsy driving, such as prior sleep behavior and road type. DBN models consist of graph structures—nodes connected by directed edges—that mimic the dependencies in the underlying problem, and an associated group of probabilities that model the likelihood of model state transitions. The dynamic components of the model specify dependencies across time (Murphy, 2002). More specifically, DBN algorithms can encode facts about drowsiness such as drivers that are drowsy are likely to stay drowsy and that drivers that are awake tend to stay awake. Specification of a DBN requires indicating the probabilities or probability distributions that characterize the relationships in the model.

Several studies have explored the utility of DBN for drowsiness detection. Ji et al. (2006) developed an algorithm that combines contextual, facial, ocular, and head-position input to predict drowsiness as defined by reaction times during a non-driving vigilance task. The contextual information in the algorithm consisted of circadian rhythm, sleep quality, the presence of sleep disorders, and information about work environments. The probability distributions for these contextual factors were inferred based on domain knowledge. Yang et al. (2010) extended the work by adding heart rate, EEG, and eye measures as input to the previous algorithm. While these studies demonstrate the potential effectiveness of the DBN framework for detecting drowsiness, they carry many of the same limitations associated with other EEG and eye-closure based algorithm and they do not consider relevant contextual aspects in drowsy driving, such as the type of road and driving maneuvers (e.g. lane changes). The studies discussed in this review are summarized in Table 1. A more thorough review can be found in Lenné and Jacobs (2016).

1.3. A temporal and contextual algorithm for drowsiness detection

The role of the type of road in drowsiness related crash risk is well established (I. D. Brown, 1994). Crashes attributed to drowsiness are significantly more common on rural straight roads that do not contain sufficient stimuli to keep the driver awake. Furthermore many studies and models of driver behavior illustrate that drivers alter their driving behavior relative to the driving context (McRuer et al., 1977; Michon, 1986; Salvucci, 2006; Weir and McRuer, 1970; Wilde, 1988). The significance of context in both unimpaired and drowsy driving behavior suggests there is a gap in the literature for drowsiness detection algorithms that include on-road contextual factors as an input. These factors may include both the type of road (residential street, highway, urban arterial) and the immediate environment around the driver (other