Closing the gap between science and practice in the prediction of drowsiness-related driving events

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Abstract

Drowsy driving remains a significant contributing factor to road crashes. This paper assesses the recent developments in the detection and prediction of drowsiness-related driving events. The research reviewed here has confirmed that drowsiness can have a serious impact on driving performance in controlled, experimental settings. New findings from on-road studies however show different impacts on performance although few studies have characterised precise relationships between drowsiness and driving performance. The measurement of drowsiness-related events has progressed and recent research suggests that subjective ratings, blink duration and steering metrics show promise in being effective predictors of drowsiness-related driving events.

Background

Driver drowsiness remains a key road safety priority, remaining one of the 'fatal five' road safety issues in Australia. While it is difficult to accurately establish the prevalence of drowsiness in crashes, estimates suggest up to approximately 18% of crashes in Australia may involve a drowsy driver (Filtness et al., In press). These crashes are typically characterised as being run-off-road crashes involving a single vehicle.

Largely driven by the automotive industry's need for embedded drowsiness solutions, detecting drowsiness while driving is now the topic of much academic research and industry development. A growing body of research attempts to link a state or level of drowsiness with a driving-related outcome. As run-off-road crashes are associated with drowsiness most research adopts a lane excursion event as the safety outcome of interest. The aim of this paper is to critically review the progress of published research in achieving the aim of linking real-time drowsiness assessments to driving outcomes.

Method

To focus on the most recent developments this paper reviewed research published from 2010 onwards using search terms that included combinations of driver drowsiness/fatigue, fatigue/drowsiness detection, fatigue/drowsiness prediction, and driver performance. Databases searched were ScienceDirect, OVID and other academic databases. Human factors studies that link vehicle-based measures with drowsiness measures were reviewed by targeting articles that included: an objective vehicle-based measure of driving performance (e.g., lane position, steering behaviour); a drowsiness manipulation (e.g., sleep loss, restricted sleep), and an associated measure(s) of drowsiness (e.g., subjective ratings, physiological measures). Research that captures algorithms and detection methods emerging from the more technology-based literature of intelligent sensing was also reviewed.

Results

The initial search yielded 49 publications. In all there were 19 studies that met the inclusion criteria (13 simulator-based, six on-road studies). Table 1 illustrates the key measures and manipulations in these simulator-based and on-road studies and notes key areas where findings differ between the two methods.

Table 1. Summary of key findings from simulator and on-road studies that link drowsiness with driving events.

Study characteristics	Simulator studies	On-Road studies	Key differences in findings
Drowsiness manipulations	Partial and full sleep loss up to 24 hours without sleep	Driving during the day and after partial sleep loss (to 5am) Driving during the day after night shift	Typically, more extreme sleep loss in simulator studies Levels of drowsiness typically lower in on-road studies compared to simulator studies
Drowsiness metrics	Karolinksa Sleepiness Scale [KSS] (subjective) Observer rating scales Psychomotor Vigilance Task (reaction time) Karolinksa Drowsiness Test / EEG Ocular metrics (PERCLOS, blink duration)	KSS(subjective) Observer rating scales EEG EOG (blink duration)	Less use of PERCLOS and EEG measures in on-road studies due historically to technical limitations associated with their measurement in the field
Driving tasks	Simulated driving for periods of between 1-2 hrs. Measurement of lane position, steering, etc at high precision	Real world driving (between 1-2.5 hrs) Test track (two hour driving sessions)	Metrics related to lane position and lane excursions are measured more accurately in simulated driving environments. Lane position measures show reduced impacts of drowsiness in on-road studies.

In addition to summary findings in Table 1, it has been found that subjective sleepiness, driving behaviour metrics and ocular metrics have been linked to the occurrence of lane departure events (e.g., Hallvig et al., 2014; Lee et al., 2015). Within the human factors literature a predictive model was recently developed based on steering wheel inputs (McDonald et al., 2014). Research published in the more technologically oriented journals uses an array of video-based and other sensing methods (e.g., Azim et al., 2014; Gurudath et al., 2014), along with a range of algorithm development methods; however they need to be trained and validated using real-world data. Drawing these two areas of research together it is possible to identify the key areas of need to take the field to the next step.

Conclusion

There has been a renewed focus on linking drowsiness with driving events and significant efforts devoted to the development of new predictive algorithms. As highlighted in Table 1, there is evidence from studies using both subjective and objective drowsiness metrics that there are differences in the way drowsiness manifests in the laboratory compared with on-road driving (Hallvig et al., 2013). This places great importance on collecting data in real driving conditions, and ideally, in naturalistic driving environments. Developments in data collection technologies now support this aim. As the automotive industry seeks embedded drowsiness detection solutions, it is the combination of new real world data collection and the emerging sensing capabilities that is likely to yield the next breakthroughs in this area.

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