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Identifying behavioural change among drivers using Long Short-Term Memory recurrent neural networks

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ABSTRACT

Globally, motor vehicle crashes account for over 1.2 million fatalities per year and are the leading cause of death for people aged 15–29 years. The majority of road crashes are caused by human error, with risk heightened among young and novice drivers learning to negotiate the complexities of the road environment. Direct feedback has been shown to have a positive impact on driving behaviour. Methods that could detect behavioural changes and therefore, positively reinforce safer driving during the early stages of driver licensing could have considerable road safety benefit. A new methodology is presented combining in-vehicle telematics technology, providing measurements forming a personalised driver profile, with neural networks to identify changes in driving behaviour. Using Long Short-Term Memory (LSTM) recurrent neural networks, individual drivers are identified based on their pattern of acceleration, deceleration and exceeding the speed limit. After model calibration, new, real-time data of the driver is supplied to the LSTM and, by monitoring prediction performance, one can assess whether a (positive or negative) change in driving behaviour is occurring over time. The paper highlights that the approach is robust to different neural network structures, data selections, calibration settings, and methodologies to select benchmarks for safe and unsafe driving. Presented case studies show additional model applications for investigating changes in driving behaviour among individuals following or during specific events (e.g., receipt of insurance renewal letters) and time periods (e.g., driving during holiday periods). The application of the presented methodology shows potential to form the basis of timely provision of direct feedback to drivers by telematics-based insurers. Such feedback may prevent internalisation of new, risky driving habits contributing to crash risk, potentially reducing deaths and injuries among young drivers as a result.

1. Introduction

Motor vehicle crashes contribute to over 1.2 million fatalities per year and up to 50 million injuries (WHO, 2013, 2015). Detailed investigation of crash statistics shows an over-representation of young adults among these figures, with those aged 15–29 particularly at risk. This over-representation has been tempered due to the introduction of various mitigating measures such as graduated licensing systems (Russell, Vandermeer, & Hartling, 2011). However, the ongoing levels of road

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trauma (both road deaths and injuries) provides impetus for new approaches and technologies that may reduce road trauma. As such, a new methodology based on in-vehicle telematics technology is presented in this research with the potential to reduce high-risk behaviour regardless of driver age.

1.1. Driving behaviour

There is a strong relationship between driving behaviour and crash risk, with exceeding posted speed limits one of the key factors related to crash risk and severity (Finch, Kompfner, Lockwood, & Maycock, 1994; Mackay & Hassan, 2000; Peden et al., 2004). Although estimates vary between studies, there is consensus that in 95–99% of crashes, a driver behavioural error either caused or contributed to the incident (e.g., Hendricks, Freedman, Zador, & Fell, 2001; Sayed, Abdelwahab, & Navin, 1995). Furthermore, driving behaviour is dynamic, changing over time (e.g., Wijnands et al., 2016). After a young driver obtains a driver's licence, driving skills improve as they learn to negotiate the complexities of the road environment (Mayhew, Simpson, & Pak, 2003).

However, crash rates do not solely depend on personal driving style, but also on when and where a vehicle is driven. For example, Paefgen, Staake, and Fleisch (2014) performed a case control study using in-vehicle data recorders, exploring associations between exposure variables and crash risk. This work demonstrated that highway driving had a lower risk per kilometre travelled than urban driving, driving during weekends was associated with lower risks, and crash risk while driving between 6 p.m. and 9 p.m. was higher than during other periods.

Current performance feedback to drivers is usually provided in the form of punishment for poor driving. For example, drivers may receive feedback on their performance from law enforcement officers for speeding or dangerous driving. This feedback may be delivered as letters, apprehensions, arrests, fines, demerit points, seizure of assets (e.g., car), or losses of licence, etc. The basic principle of this form of feedback known as operant conditioning (Nevin, 1969) is that the driver will learn to associate their poor driving behaviour with an aversive consequence (e.g., the punishment), which then reduces or halts the poor behaviour.

Learning within operant conditioning models works best when associations between antecedents (the environment), behaviours (the actions of the individual) and consequences (the reward or punishment) are delivered in a manner that enables clear, timely connection between stages of the reinforcement regime to be recognised by the individual (Ammons, 1956). Ideally, these principles should also be inherent within road safety enforcement regimes (Fildes, Langford, Andrea, & Scully, 2005).

For example, in the case of fixed speeding cameras, drivers may receive notification of punishment weeks after they have committed an offence, reducing opportunity to link behaviour and consequences in a timely manner. Such issues have potentially contributed to levels of distrust among sub-populations of the community in relation to the legitimacy of such enforcement programs (Fleiter & Watson, 2012). Further, existing regimes largely ignore the complementary side of the operant conditioning model known as 'positive reinforcement' or more simply 'reward' (Fleiter, Watson, Lennon, King, & Shi, 2009). This limitation may further weaken the ability of existing punishment-based systems to positively influence driver behaviour. To this point, however, it has been difficult for enforcement authorities to identify behaviours with sufficient sensitivity to recognise small changes in either positive or negative driving behaviour that provide opportunity for reinforcement.

1.2. In-vehicle telematics

A new technology that has the potential to improve driving behaviour is in-vehicle telematics. In-vehicle telematics technology forms the basis of an emerging insurance product, commonly referred to as Pay-As-You-Drive (PAYD) insurance (e.g., Bordoff & Noel, 2008). In these schemes, insurance premiums are determined based on actual driving behaviour of policy holders, which are captured by accessing information from internal vehicle systems or location tracking, rather than a comparison to claims of similar drivers. As such, in-vehicle telematics may provide a more sensitive and effective means through which positive driving behaviour can be shaped.

Evidence is emerging regarding the utility of using in-vehicle telematics technology in improving road safety through provision of financial incentives or direct driver feedback. For example, Bolderdijk, Knockaert, Steg, and Verhoef (2011) showed that PAYD insurance incentives for young drivers, opting to participate in the experiment, significantly reduced speed limit violations. Furthermore, Dijksterhuis et al. (2015) found a significant reduction in at-risk driving using low value incentives.

A systematic review by the Transport Research Laboratory on the effects of PAYD insurance provides various recommendations for future research on in-vehicle telematics (Tong et al., 2016); e.g., an investigation of the effects of different types of feedback. In general, Donmez, Boyle, and Lee (2008) confirmed the positive impact of feedback on driving behaviour. However, Prato, Toledo, Lotan, and Taubman-Ben-Ari (2010) found that feedback based on in-vehicle data recorders only temporarily decreased risky behaviour for young, male drivers. Furthermore, the most effective way to deliver feedback in the context of driver behaviour is still uncertain (Horrey, Lesch, Dainoff, Robertson, & Noy, 2012). Feedback should be timely, as argued earlier, however, reporting to the driver post-journey has been shown to be only slightly less effective than in-car feedback (Dijksterhuis et al., 2015). Lahrmann et al. (2012) investigated the feasibility of a market introduction of an Intelligent Speed Adaption system that provides verbal warnings every six seconds when speeding. The study experienced major