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Detection of driver drowsiness using wearable devices: A feasibility study of the proximity sensor

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ABSTRACT

Background: Drowsiness is one of the major factors that cause crashes in the transportation industry. Drowsiness detection systems can alert drowsy operators and potentially reduce the risk of crashes. In this study, a Google-Glass-based drowsiness detection system was developed and validated.
Methods: The proximity sensor of Google Glass was used to monitor eye blink frequency. A simulated driving study was carried out to validate the system. Driving performance and eye blinks were compared between the two states of alertness and drowsiness while driving.
Results: Drowsy drivers increased frequency of eye blinks, produced longer braking response time and increased lane deviation, compared to when they were alert. A threshold algorithm for proximity sensor can reliably detect eye blinks and proved the feasibility of using Google Glass to detect operator drowsiness.
Applications: This technology provides a new platform to detect operator drowsiness and has the potential to reduce drowsiness-related crashes in driving and aviation.

1. Introduction

1.1. Risks of drowsiness

Drowsiness significantly increases the risk of crashes in driving and aviation. The AAA Foundation for Traffic Safety surveyed over 14,000 crashes from 2009 to 2013 and estimated that drowsiness was involved in 21% of the fatal crashes (Tefft, 2014). Similarly, the National Transportation Safety Board estimated that drowsiness was involved in up to 21% of self-reported crashes in the aviation industry (Akerstedt et al., 2003).

Despite these risks, drivers continue to drive even when they are drowsy. A survey study by the National Sleep Foundation showed that 54% of adult drivers admitted to driving a vehicle while drowsy (National Sleep Foundation, 2010). A previous survey study showed that as many as 37% of adult drivers admitted that they fell asleep behind the wheel, of which, 13% of them did so on a monthly basis (National Sleep Foundation, 2005). This may not be that surprising since 48% of Americans don't get enough sleep due to early morning/night shifts and unusual work schedules (Åkerstedt, 2003; Allen et al., 2014; Härmä et al., 1998; Stutts et al., 2003), and long monotonous tasks like driving are highly susceptible to the effects of sleep deprivation (Papadelis et al., 2006).

1.2. Impact of drowsiness

The impact of drowsiness on driving is comparable to drunk driving (De Waard and Brookhuis, 1991; Williamson and Feyer, 2000). Drowsiness can lead to impaired ability to perceive visual information (Hancock and McNaughton, 1986; National Sleep Foundation, 2010), lack of attention towards the driving environment, vigilance decrements (Bourgeois-Bougrine et al., 2003;

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Brown, 1994), and slower reaction time (National Sleep Foundation, 2010; Ueno et al., 1994). Drowsy drivers are also more likely to have lapses in judgment and delays in information processing (Lyznicki et al., 1998; National Sleep Foundation, 2010). Drowsy drivers typically have more unstable driving performance (Ting et al., 2008; Thiffault and Bergeron, 2003), for example, higher speed variability (Fairclough and Graham, 1999), impaired responses to speed changes of the vehicle in front of them (De Waard and Brookhuis, 1991), more instability in lane keeping, and potentially major lane departures (De Waard and Brookhuis, 1991; Fairclough and Graham, 1999; Ingre et al., 2006).

1.3. Factors contributing to drowsiness

Many factors may lead to drowsiness, such as sleep hygiene, time of day, age, physical fitness, and alcohol consumption (Härmä et al., 1988; Härmä et al., 1998). For example, drivers who had drowsiness-related crashes were more likely to have poorer sleep quality, have multiple jobs, and drive for longer amounts of time (Stutts et al., 2003). Nighttime driving can be up to 3 to 6 times more dangerous than daytime driving (Akerstedt et al., 2001; Varghese and Shankar, 2007). In addition to the low visibility during nighttime driving, there is an increased sleep tendency and decreased cognitive function during 2–7 A.M., regardless of sleep schedule (Mitler et al., 1988).

Overconfidence in level of alertness may also amplify the risks of drowsy driving. Drivers often underestimate how drowsy they really are (Brown, 1994; Itoi et al., 1993; Mitler et al., 1988). Most adults try to compensate for lack of sleep using various methods, such as drinking coffee, but overestimate the effectiveness of these methods (Mitler et al., 1988).

1.4. Approaches to detecting drowsiness

Different approaches have been investigated to detect drowsiness, including computer vision algorithms observing facial and eye images, wearable sensors to monitor physiological measurements, and driving dynamics.

Computer vision technology is a non-intrusive method to monitor drowsiness. It uses one or multiple cameras to monitor driver's face and eye images (Azim et al., 2014). Eye-tracking can be seen as a special case of computer vision based drowsiness detection which focuses on drivers' eye movements, especially eye blink and percentage of eye closure. Eye blink is directly associated with drowsiness (For example, see Caffier et al., 2003; Chen et al., 2014; Ganage and Dixit, 2011; Jayasundera et al., 2014; Kurylyak et al., 2012). Eye blink is often detected using advanced computer vision together with devoted and specially-designed camera. For example, Kumar and Bhowmick (2009) used an IR camera to detect eye blinks by tracking pupil. Pathangay et al. (2016) used an RGBD camera to detect drowsiness by combining eye blinks/eye closure and heart rate. The combined computer vision algorithm with devoted camera approach suffers from many limitations. For example, the camera system cannot reliably detect face, eye, and eye blinks at nighttime, for unevenly lighted faces, and for dark skin colored users. Users are not very willing to purchase expensive devoted system to monitor drowsiness. Thus, in this article, we proposed a new wearable proximity-sensor approach to detect eye blinks and drowsiness, in a hope to address the limitations of the camera-based blink/drowsiness detection system.

Despite the benefit of non-intrusiveness, computer-vision-based drowsiness detection often requires expensive cameras and infrared illuminators (He, 2013). In addition, lighting conditions, car vibration, and head tilting can pose further challenges to the computer vision algorithms (Azim et al., 2014; He et al., 2014). Advanced machine learning algorithms are often needed to supplement the computer vision algorithms in uncertain environments (Deng et al., 2016a) and to handle images with noise and illumination changes (Deng et al., 2012).

Physiological measures, such as brain waves, heart rate, respiration and skin conductance, often provide high precision results for drowsiness detection (Bergasa et al., 2006). Electroencephalograms (EEG) can be used to detect driver drowsiness by monitoring the amplitude of brain waves (Kong et al., 2012). Gamma waves, in particular, are used to measure level of drowsiness (Kong et al., 2012). This method is considered to be highly reliable since the brain waves are closely associated with mental and physical activities (Kar et al., 2010; Kong et al., 2012).

However, the brain wave approach requires electric nodes, which are uncomfortable, expensive, and difficult to use in real-world driving (Azim et al., 2014; Healey and Picard, 2005). Heart rate has also been shown to be indicative of drowsiness. Heart rate decreases and heart rate variability increases when drivers are drowsy (O'Hanlon and Kelley, 1977; Helander, 1978; Egelund, 1982; Lal and Craig, 2002; Rogado et al., 2009). Heart rate variability alone was able to detect drowsiness with an accuracy rate of 90% (Patel et al., 2011). Flat and slow respiration rate is another indicator for drowsiness (Bundele, 2008; Bundele and Banerjee, 2009; Krajewski et al., 2008). Galvanic skin response, measured by electrical conductance on skin and an indicator of autonomic nervous system activation (Healey and Picard, 2000), can also contribute to the drowsiness detection.

These physiological indicators can be combined to create a comprehensive detection method for drowsiness (Bundele and Banerjee, 2009). However, these measures are often collected by placing sensors on the body and can be uncomfortable (Azim et al., 2014). Also, physiological measurements like heart rate depend on individual differences such as age and health status, which makes it challenging to create a model that can be generalizable to all users. Moreover, the noise from car vibration, body movement and insecure attachment of sensors during driving pose further challenges in signal processing for satisfactory system accuracy.

Driving dynamics, such as lane position and steering behavior, can serve as another approach for drowsiness detection (Azim et al., 2014; Rimini-Doering et al., 2001). While this method is not intrusive, it is hard to generalize the machine-learning model based on driving dynamics to various drivers, vehicle types and road conditions (Azim et al., 2014).

See Table 1 for comparisons of various approaches to monitoring drowsiness.

1.5. Google Glass

The recent boom of wearable devices (such as Google Glass and J!NS MEME) (Ishimaru et al., 2014b) provides new platforms to develop more practical drowsiness detection technologies. Google Glass may be a more practical, more reliable and faster approach than a camera-based system (He, 2013). Google Glass sensors (i.e. accelerometer and proximity) can be sampled at over 100 Hz, much faster than an average camera or smartphone cameras, which is usually around 15 Hz. Google Glass sensors are also more reliable than computer-vision algorithms, which often perform poorly under low lighting conditions and depend heavily on users' skin, eye color, and head tilt angle. Moreover, Google Glass and other wearable devices with proximity sensors (such as Vigo smart Bluetooth device) are multiple-purpose devices. Device owners may have purchased Google Glass for many other reasons, such as for texting (Wu et al., 2016; He et al., 2015), GPS navigation (Beckers et al., 2017), and hands-free calling. If it is feasible to detect drowsiness with wearable proximity sensors, the drowsiness

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