Applied Ergonomics 65 (2017) 473–480

Contents lists available at ScienceDirect

Applied Ergonomics

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

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

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A R T I C L E I N F O

Article history:
Received 14 June 2016
Received in revised form
3 January 2017
Accepted 22 February 2017
Available online 15 April 2017

Keywords:
Driver drowsiness
Wearable device
Proximity sensor

A B S T R A C T

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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http://dx.doi.org/10.1016/j.apergo.2017.02.016
0003-6870/

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

Table 1
Comparisons of various approaches to monitor drowsiness.

Sensors	Dependent Variables	Advantages	Limitations	Citations
Eye-tracking	Eye blinks	- Non-intrusive - Comprehensive indicators	- Costly - Noise (glasses, head movements, etc.)	Azim et al., 2014; He et al., 2014; Yang et al., 2012
Accelerometer Sensors	Head movements	- Low intrusiveness - Low cost	- Noise from sensor location and car vibrations	Amini et al., 2011; Dong et al., 2014
EEG	Brain's electrical activity	- Reliable - High temporal resolution	- Costly - Uncomfortable - Environmental artifacts (e.g. head movement)	Azim et al., 2014; Kar et al., 2010; Kong et al., 2012
Heart Rate	Heart rate	- High accuracy - Low cost - Low intrusive	- Confounded by age and health, exercise	Rogado et al., 2009; Patel et al., 2011;
Respiration Rate	Respiration rate	- High accuracy	- Sensor may slip - Uncomfortable	Bundele, 2008; Healey and Picard, 2005
Galvanic Skin Response	Skin conductance	- Easy to attach	- Noises from environmental weather	Bundele and Banerjee, 2009; Steele et al., 2004
Driving Dynamics	Lane position, speed etc	- Nonintrusive - Easily accessible - Low cost	- Noise (vehicle type, road condition, etc.) - Generalizability	Azim et al., 2014
Proximity Sensor	Eye blinks	- Low cost - Reliable - Commercially available	- Cannot track eye movement, such as fixation duration	Ishimaru et al., 2014a,b

system will cost nothing or only a small software service fee for users with existing ownership of Google Glass. This potential huge reduction of the cost, improvement of reliability, and reduction of intrusiveness may make drowsiness detection system begins to be popular among drivers. However, the utilization of proximity sensors to detect drowsiness is new and has not been scientifically studied yet.

This project used the sensors of Google Glass to monitor the frequency of eye blinks. A simulated driving study was also conducted to explore the feasibility of using the proximity sensor to monitor driver drowsiness.

2. Methods

2.1. Participants

Twenty-three experienced drivers (including 13 females and 10 males) were recruited by posters and online advertisements ($M = 25.0$ years of age, $SD = 3.7$ years). All participants had a valid driver license. To qualify for the study, participants had to have at least three years of driving experience, with normal or corrected to normal vision ability, no medical constrain, and no motion sickness, alcoholism, drug abuse. Participants were allowed to wear contact lenses, but they were not allowed to wear spectacles since they would interfere with Google Glass. Participants were asked to avoid caffeine and tea for four hours before the study and to avoid alcohol for 24 hours before the study. The study happened in the time frame from 8am to 8pm.

2.2. Apparatus and tasks

The driving scenarios were created using HyperDrive Authoring Suite™ Version 1.6.1 and Drive Safety's Vection Simulation Software™ Version 1.6.1. The driving simulator consisted of three 26″ ASUS monitors (1920 × 1080). Drivers sat approximately one meter away from the front monitor, at a visual angle of 75.55°. The monitors simulated the driving environment through front and side windows. Vehicle dynamics were sampled at 60 Hz. The simulator used a Logitech Driving Force GT steering wheel and pedals for driving operation input. Fig. 1 depicts the driving simulator.

Google Glass is a monocular optical Head-Mounted Display

Fig. 1. HyperDrive driving simulator with driver wearing Google Glass.

(HMD), which is similar to a 25″ high definition screen viewed from eight feet away. The display was placed in front of the right eye, and the participants were allowed to adjust the display to the angle they were most comfortable with. Google Glass was worn like a regular pair of spectacles. Google Glass had a 1.2 GHz dual core processor and 640 × 360 resolution display. They wore Google Glass during all the experimental conditions. Please see Fig. 2 for an example of Google Glass.

There is a built-in proximity sensor in Google Glass pointing towards the wearer's right eye. When the eyes blink, the readings of the proximity sensors will change accordingly. See Fig. 4 for a demo of the proximity sensor value in a sample eye blink event. We used a threshold algorithm to detect eye blinks (Ishimaru et al., 2014a). The thresholds for eye blinks events were calibrated individually (see Fig. 4).

The infrared proximity sensor in Google Glass (as shown in Fig. 3) was commonly used in smartphones. The proximity sensor emits infrared lights and monitors the amount of reflected infrared light to calculate the distance to objects. During an eye blink event, the eyelid will change the distance of the infrared proximity sensor to the eye, thus causing a spike in the vector of the proximity sensor value (as shown in Fig. 4). A moving time window with a window width of 2 s was used to learn the optimal thresholds for eye blinks.

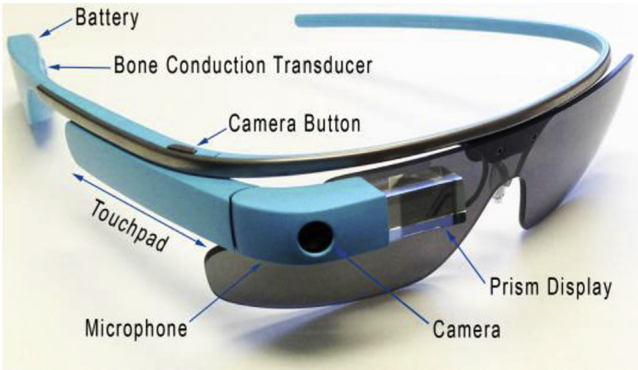

Fig. 2. Google Glass with structure labels.

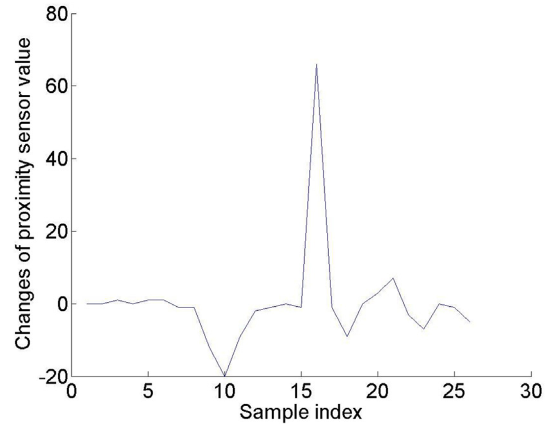

Fig. 4. The changes of the proximity sensor value during an eye blink event.

Each data point within the time window was mean-centered as the sensor value minus the average of all sensor values in the time window (Ishimaru et al., 2014a). Based on former research, the threshold for eye blinks was set in the range of 3.0–7.0 (Ishimaru et al., 2014a). The optimal threshold was calculated with a step of 0.1 ranging from 3.0 to 7.0 for each participant.

Two scales were used to estimate the level of sleepiness of the participants. The Stanford Sleepiness Scale is a one-item scale for sleepiness in a given moment (Hoddes et al., 1973). The Karolinska Sleepiness Scale is a one-item scale developed by the Karolinska Institute and is a quick measure of "state" sleepiness (Akerstedt and Gillberg, 1990). The Stanford Sleepiness Scale has been shown to be sensitive to deficits in alertness (Herscovitch and Broughton, 1980) and the Karolinska Sleepiness Scale has been used in several studies to measure driver drowsiness (Kozak et al., 2005). The two scales measure how sleepy a person is in a given moment. Please refer to Appendix for detailed information about the scales.

2.3. Driving task

A standard car-following task on a straight three-lane freeway was used to measure driving performance, as rear-end collision is one of the most common types of crashes and frequently used in simulator-based driving studies (He et al., 2014; Strayer et al., 2003). Participants were instructed to follow a leading vehicle with a two-second headway time. Both the participant and the leading vehicle stayed in the center lane. The leading vehicle drove at a speed of 55 miles per hour (mph) and braked at random time intervals. We instructed the participants to brake as soon as the leading vehicle braked.

Lateral wind gusts were simulated randomly every three to eight seconds with duration of up to three seconds. The strength of the lateral winds ranged from 1000 to 2000 N. Participants were instructed to adjust their lane positions whenever they noticed the car deviated from the center of the middle lane.

2.4. Procedure

Upon arrival at the lab, participants first signed an informed consent form, then filled out a demographic survey, and passed a vision ability test. They were then instructed to practice driving in the simulator for 10 min while wearing Google Glass. The participants were instructed to blink their eyes as soon as they heard an auditory prompt of beeping from Google Glass. Each event was carried out 20 times while the proximity sensor and accelerometer sensor value logged at 50 Hz by a customized Google Glass application. These values collected in the calibration procedure were used to determinate the individual-based thresholds to detect eye blinks. This threshold algorithm has been commonly used for event detection (Ishimaru et al., 2014a,b), and was inspired by the wink detection feature of Google Glass.

When the participants became comfortable with the driving task, they self-evaluated their drowsiness states using both the Karolinska Sleepiness Scale and Stanford Sleepiness Scale. They then drove in three driving sessions continuously, each lasting 30 min. The first, second and third sessions were labeled as short-drive, medium-drive, long-drive sessions hereafter. At the end of each driving session, they reported their drowsiness states again. Eye blinks and vehicle dynamics were automatically recorded by the Google Glass and the HyperDrive simulation software respectively. The experiment lasted for about three hours. At the end of the studies, participants were paid at $10 per hour for their participation.

2.5. Data analysis

Driving performance was assessed using the braking response time, the mean headway distance, the standard deviation of lane position (SDLP) and the number of lane excursions. Brake response

Fig. 3. Demonstration of the proximity sensor in Google Glass and iPhone.

time was measured from the onset of the lead vehicle braking until the initiation of a braking response by participant vehicle. A brake response was operationally defined as a minimal depression of 1% of the brake pedal (Strayer et al., 2006). A lack of braking response was defined as a failure to brake within 5 s after the lead vehicle braked. Headway distance was measured from the rear end of the lead vehicle to the front bumper of the subject vehicle. Larger values of SDLP indicated poorer lane-keeping performance and higher risk of lane departure. A lane excursion was defined as a shift to a new lane for less than three seconds followed by a return to the previous lane.

All dependent variables were submitted to repeated-measure analyses of variance (ANOVA) with drive sessions (short, medium and long drive sessions) as the only within-subject factor. IBM SPSS v18.0 was used in the statistical analysis. Bonferroni adjustments were included to correct for multiple comparisons. Mean differences were considered significant at the 0.05 alpha level.

3. Results

3.1. Self-reported drowsiness

Participants drove 90 min in the formal simulated driving sessions. Due to the monotonous scenario and dark environment in driving simulators, it takes shorter period to induce driver drowsiness. An earlier study also observed significant drowsiness effects within 50 min of test trial in a driving simulator (Eoh et al., 2005). The average self-reported drowsiness level at the last session is 6.46 with a range from 3.67 to 9 for the Karolinska Sleeping Scale. The average self-reported drowsiness level at the end is between 6 (Some signs of sleepiness) and 7 (Sleepy, but no effort to keep alert). This indicates our study manipulation has successfully induced drowsiness.

The self-reported drowsiness in the Karolinska Sleepiness Scale (as shown in Fig. 5) revealed a significant main effect of driving sessions, $F\ (2, 44) = 57.33$, $p < .001$, $\eta^2_p = 0.72$. The self-reported drowsiness rating was lowest in the short-drive session ($M = 4.26$, $SD = 1.20$) compared to the medium-drive ($M = 5.34$, $SD = 1.28$) and long-drive session ($M = 6.46$, $SD = 1.28$), $t\ (22) = 5.96$, $p < .001$ and $t\ (22) = 8.71$, $p < .001$ respectively. The drowsiness rating in the medium-drive session was also lower than that in the long-drive session, $t\ (22) = 6.51$, $p < .001$. The self-reported drowsiness measured by the Stanford Sleepiness Scale produced similar results. Thus, the self-reported drowsiness for the Karolinska Sleepiness Scale indicated that our experiment manipulation was successful to incur states of drowsiness.

3.2. Eye blinks

The blink frequency per minute (bpm) (as shown in Fig. 6.) produced a main effect for the driving sessions, $F\ (2, 44) = 5.22$, $p = .009$, $\eta^2 = 0.19$. Pair-wise comparisons showed that the blink frequency was smaller in the short-drive ($M = 10.46$ bpm, $SD = 3.93$bpm) and medium-drive ($M = 11.03$ bpm, $SD = 3.15$ bpm) than the long-drive session ($M = 11.79$ bpm, $SD = 2.78$bpm), $t\ (22) = 3.27$, $p = .004$ and $t\ (22) = 2.08$, $p = .05$ respectively. Higher blink frequency was observed in long-drive session, indicating higher levels of drowsiness.

3.3. Braking response time

The braking response time showed a main effect for the driving sessions, $F\,(2, 44) = 3.77$, $p = .031$, $\eta^2 = 0.15$. As shown in Fig. 7, the braking response time increased as driving duration increased. Pair-wise comparisons showed that the braking response time in short-drive session ($M = 1.19$s, $SD = 0.23$s) was significantly lower than that of long-drive session ($M = 1.33$s, $SD = 0.28$s), $t\,(22) = 3.34$, $p = .003$. The braking response time in medium-drive session ($M = 1.25$s, $SD = 0.35$s) and short-drive session did not differ from each other, $t\,(22) = 1.18$, $p = .25$, nor did medium-drive session and long-drive session, $t\ (22) = 1.36$, $p = .19$.

3.4. Headway distance

The mean headway distance (as shown in Fig. 8.) did not produce a main effect for the driving sessions, $F\,(2, 44) = 0.9$, $p = .92$, $\eta^2 = 0.004$. Pair-wise comparisons showed that the mean headway distance did not differ among driving sessions, all $ps > 0.10$.

3.5. Standard deviation of lane position

The standard deviation of lane position (SDLP) produced a main effect for the driving sessions, $F\,(2, 44) = 5.25$, $p = .009$, $\eta^2 = 0.19$. As shown in Fig. 9, SDLP gradually increased as driving duration increased. Pair-wise comparisons show that SDLP in short-drive session ($M = 0.40$ m, $SD = 0.07$ m) was significantly lower than that of medium-drive session ($M = 0.44$ m, $SD = 0.11$ m) and long-drive session ($M = 0.45$ m, $SD = 0.09$ m), $t\,(22) = 2.47$, $p = .02$ and t

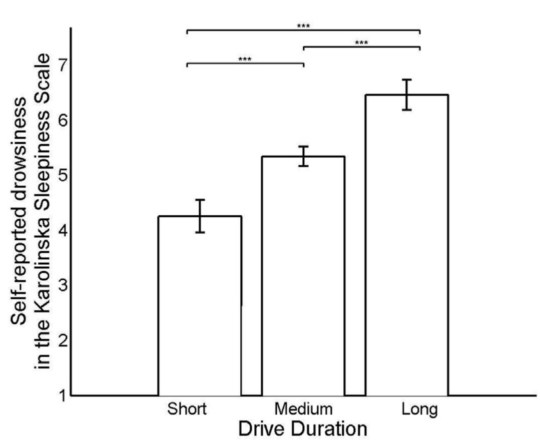

Fig. 5. Self-reported drowsiness in the Karolinska Sleepiness Scale. (The stars indicate significance level. * represents $p \le .05$; ** represents $p \le .01$; *** represents $p \le .001$. This applies to stars in other graphs in this article).

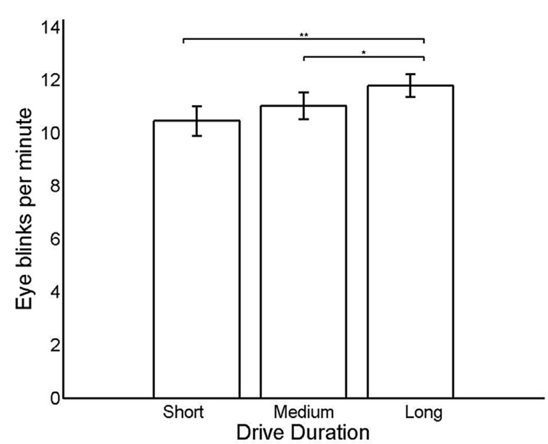

Fig. 6. Blink frequency as time increases. Error bars in all figures hereafter indicate within-subject 95% confidence intervals based on the main effect of task (Loftus and Masson, 1994).

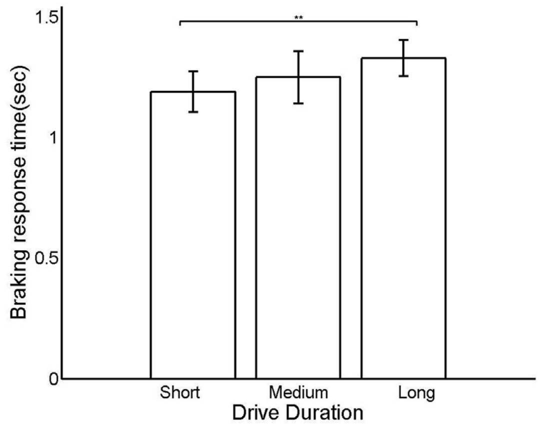

Fig. 7. Braking response time as drive duration increases.

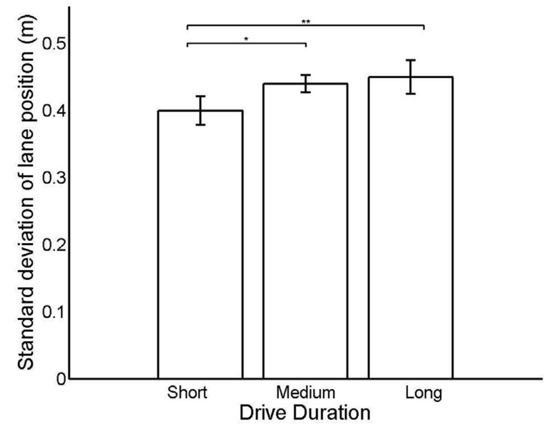

Fig. 9. Standard deviation of lane position as time increases.

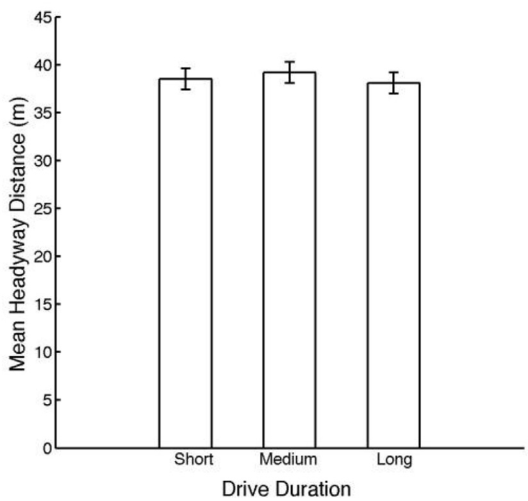

Fig. 8. Mean headway distance as time increases.

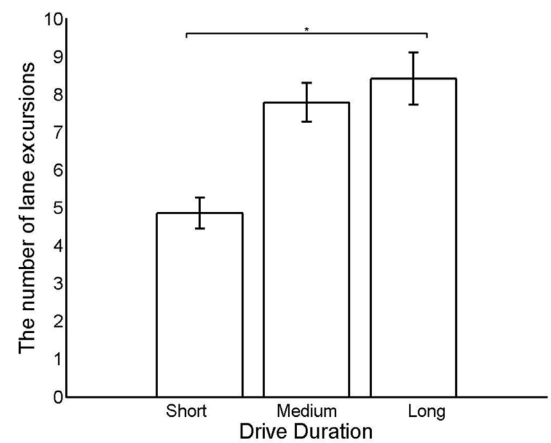

Fig. 10. Number of lane excursions as time increases.

(22) = 3.31, p = .003 respectively. The SDLP in the medium-drive session did not differ from long-drive session, t (22) = 0.70, p = .49.

3.6. Lane excursions

The number of lane excursions produced a main effect for the driving sessions, F (2, 44) = 3.16, p = .05, $\eta^2 = 0.13$. As shown in Fig. 10, the number of lane excursions gradually increased as driving duration increased. Pair-wise comparisons showed that the number of lane excursions in short-drive session (M = 4.87, SD = 3.53) was significantly lower than that of long-drive session (M = 8.43, SD = 8.44), t (22) = 2.17, p = .04. The number of lane excursions in medium-drive session (M = 7.80, SD = 9.27) did not differ from short-drive session, t (22) = 1.70, p = .10, nor did medium-drive session and long-drive session, t (22) = 0.58, p = .57.

4. Discussions and conclusions

To reduce the risks of driver drowsiness, we developed a Google Glass application to monitor eye blinks. Past research has shown that drowsiness can increase hazard response times and cause poorer driving performance (Bourgeois-Bougrine et al., 2003; Ting et al., 2008; Thiffault and Bergeron, 2003; He et al., 2014; Lee et al., 2016). In this study, drowsy drivers produced longer braking response time, lower braking response rate, more lane deviation, and a higher number of lane excursions. These results resonate with past studies and indicate higher risks of rear-end collisions and lane-departures (He et al., 2014; Lee et al., 2016). Previous research has shown that distracted drivers may adopt a compensatory strategy for risky distracted driving by increasing their headway distance from the lead vehicle to decrease the chances of a collision (He et al., 2014). Can drowsy drivers exhibit similar compensatory strategy employed by distracted drivers? The drowsy drivers in this study did not exhibit such compensatory strategy, producing similar headway distance across driving sessions. Thus, insufficient or lack of compensatory strategy, such as no increase in headway buffers, may put drowsy drivers at higher risks, compared to distracted drivers.

Due to the dangers of drowsiness, it is important for drivers to adopt safer strategies, such as avoiding night-time driving, alcohol and medication, avoiding rushing to destinations, getting a proper amount of sleep, and consuming caffeine (National Sleep Foundation, 2010), or taking longer breaks at rest stops (Philip et al., 1999).

Unfortunately, even if these strategies were adopted, drivers often misjudge just how sleepy they are (Brown, 1994; Itoi et al., 1993; Mitler et al., 1988) and may still be under the risk of drowsy driving. A sensitive and user friendly drowsiness detection system can reduce the risk by issuing early warnings to alarm the drivers and make them aware that they are putting themselves in danger. This is particularly important for professional drivers (e.g.

truck, bus and taxi drivers) who are quite prone to falling asleep behind the wheel, due to long driving hours and overconfidence about their driving skills.

However, existing drowsiness detection systems (e.g. eye-tracking and EEG) are often limited by the price, intrusiveness, and practicality. Several of the current drowsiness detection methods require purchasing special equipment and placing sensors on the driver. This Google-Glass-based drowsiness detection technology provides a portable and affordable alternative to existing drowsiness detection systems. It may also be more accessible and popular to users with the coming age of wearable technology. Google Glass is comparatively easier to set up than most other drowsiness detection technology. And unlike other drowsiness detection systems, Google Glass has several other functions such as texting and GPS navigation, which may increase incentive to purchase and use it.

There were limitations with this initial study, such as only using subjective rating scales to measure drowsiness. Future studies should further validate this application by using objective measures (e.g. brain waves) and comparing it to other drowsiness detection technology (e.g. proximity sensors). Future studies should also test the Google Glass application in real world driving settings. The vehicle dynamics and road unevenness may add more noise to the proximity sensor value and thus require adaptation of the thresholding algorithm to detect eye blinks. Future algorithm development efforts may consider emerging machine-learning algorithms, such as reinforcement learning and deep learning, to improve the prediction performance of algorithms across participants and driving scenarios. For example, a recent study demonstrated that the reinforcement deep neural network algorithm could train an agent to self-explore an unknown environment and thus has great potential to be applied to real-world driving conditions (Deng et al., 2016b). More over, it would be interesting to test our proposed approach using wearable proximity sensor to detect eye blinks and drowsiness with a broader age range and examine the technology acceptance levels of drivers at different age.

The Google-Glass-based drowsiness detection technology is also limited by the fast battery consumption. When using the app, Google Glass needed to be charged every three hours. The battery limitation of the Google Glass may become less problematic as battery technology advances over time. Another limitation is that blink detection is difficult for drivers wearing corrective lens or sunglasses. Eyewear technology should be further improved to have longer battery life and a higher number of proximity sensors. Future technology improvement for the system may consider adding electroencephalogram sensor to wearable glasses.

This research contributes to the efforts of detecting driver drowsiness by providing new technology for real-time drowsiness detection using Google Glass. This technology has important implications for improving driving safety. Since drivers often misjudge how drowsy they are, this system allows them to better assess the level of risk they are at and properly compensate for it.

Acknowledgements

We appreciated the funding from Vigo Technologies Inc. and the Award for Research/Creative projects from Wichita State University. We also are thankful for the data collection effort by Long Wang.

Appendix

Stanford Sleepiness Scale (*Herscovitch and Broughton, 1980*)

Please circle the item which best describes your current sleepiness level.

1 = Feeling active, vital, alert, or wide awake
2 = Functioning at high levels, but not at peak; able to concentrate
3 = Awake, but relaxed; responsive but not fully alert
4 = Somewhat foggy, let down
5 = Foggy; losing interest in remaining awake; slowed down
6 = Sleepy, woozy, fighting sleep; prefer to lie down
7 = No longer fighting sleep, sleep onset soon; having dream = like thoughts

Karolinska Sleepiness Scale (*Akerstedt and Gillberg, 1990*)

Please circle the item which best describes your current sleepiness level.

1 = Extremely alert
2 = Very alert
3 = Alert
4 = Rather alert
5 = Neither alert nor sleepy
6 = Some signs of sleepiness
7 = Sleepy, but no effort to keep alert
8 = Sleepy, some effort to keep alert
9 = Very sleepy, great effort to keep alert, fighting sleep.

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