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Lane heading difference: An innovative model for drowsy driving detection using retrospective analysis around curves

Drew M. Morris, June J. Pilcher *, Fred S. Switzer III

Department of Psychology, Clemson University, Clemson, SC, USA

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ABSTRACT

Driving while sleepy is a serious contributor to automobile accidents. Previous research has shown that drowsy drivers produce systematic errors (variability) in vehicle behavior which are detectable using vehicle monitoring technology. The current study developed a new methodological approach using a vehicle heading difference metric to detect drowsy driving more effectively than other more commonly used methods. Twenty participants completed a driving scenario as well as several measures of fatigue in five testing sessions across a night of sleep deprivation. Each simulated highway driving session lasted 20 min, and was analyzed for lateral lane position variability and vehicle heading difference variability with two statistical methods. Fatigue measures monitored reaction time, attention, and oculomotor movement. The results showed that examining lane heading difference using the absolute value of the raw data detected driving variability better across the night than other statistical models. The results from the fatigue measures indicated an increase in reaction time and response lapses, as well as a decrease in oculomotor reactivity across the night. These results suggest that in fatigued drivers the statistical model using the absolute value of lane heading could be an improved metric for drowsy driving detection that could accurately detect detriments in driving ability at lower levels of fatigue.

1. Introduction

Drowsy driving is an increasing concern in many modern societies. As such, effective drowsy driving detection technology is growing in popularity and functionality. To date, a variety of intelligent information systems have been integrated in an attempt to monitor vehicle and driver performance, yet detection systems are still in need of advancements to improve on shortcomings (Vitabile et al., 2011).

Drowsiness while driving contributes to automobile accidents. A U.S. based analysis of naturalist driving showed that drowsy drivers are five times more likely to be involved in a crash or near crash situation than alert drivers (Klauer et al., 2006). Drowsy driving also results in an estimated 56,000 crashes annually and over 40,000 fatal and non-fatal injuries (Royal, 2003). Perhaps more troubling is the finding that driving experience plays little or no role in these crash statistics. It is estimated that of the 7.5 million drivers that nod off each month, the majority are experienced drivers between the ages of 21 and 64 (Royal, 2003).

Perhaps one of the most dangerous aspects of drowsy driving is how inadequate drivers are at noticing their own sleepiness. Although thirty-seven percent of drivers admit to having fallen asleep behind the wheel, research has shown that drivers are poor at subjectively gauging their own sleepiness before being involved in an accident (Reyner and Horne, 1998; Royal, 2003). Furthermore, drowsiness-related accidents often occur within the first three hours of driving, before a person would often feel a need to break from driving, and are prevalent in the early morning when roads are often busy with daily commuters (Pack et al., 1995; Royal, 2003).

These early morning accidents are in part due to the driver's circadian rhythms of wakefulness. Circadian rhythms act as a homeostatic mechanism to regulate sleep patterns and encourage drowsiness at specific times of day (Dijk and Czeisler, 1995). When a driver does not receive a normal night of sleep, circadian rhythms interfere with performance by encouraging sleepiness and impairing neurological functioning needed for safe driving (Powell et al., 2001). Because of this impairment, people make increased errors in decision making and reaction responses. This error making tendency puts drivers at risk for accidents, and may become more pronounced while operating a vehicle at higher

* Corresponding author at: Department of Psychology, 418 Brackett Hall, Clemson University, Clemson, SC 29634-1355, USA. Tel.: +1 865 656 4985; fax: +1 864 656 0358.
E-mail address: jpilche@clemson.edu (J.J. Pilcher).

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speeds where precise actions are required. In particular, highway driving requires significant cognitive motor skills for information processing, rapid selection, and visual-spatial ability (Shinar, 1993; Ting et al., 2008). Moreover, if the driver has nodded off, waking before the accident occurs may not be enough to prevent a collision. Research has shown that the moments after waking from sleep is characterized by severe cognitive performance decline, resulting in driving variability and error even after a driver has regained situational awareness (Bonnet, 1985). Therefore, to provide a warning of the danger of drowsiness before the driver falls asleep, driver detection technology should be used to supplement a driver's sense of sleepiness early on.

Research into technology that can detect these behavioral and psychophysiological indicators of sleepiness has received attention in the past decade. Indicators of sleepiness most often index either the moving behaviors of the vehicle or the physiological characteristics of the driver that correlate with drowsiness. Using these two broad methodological approaches of assessing the progression of sleepiness, the consumer automotive market has introduced both simple and complex detection systems (Forsman et al., 2013; Ting et al., 2008). The simple detection systems often use one method of monitoring the driver or vehicle, referred to as an individual indicator. Together, combinations of individual indicators can be used in conjunction with other individual indicators to form complex detection systems. However, research has shown that complex systems may only provide negligible improvement over using a single indicator (Sandberg et al., 2011a). In addition, the individual differences among drivers may have a confounding effect on complex systems, and can take into account too many *if*s to detect drowsiness if all the right conditions are not met. The issue of over complexity and ifs demonstrates the advantage of implementing a single indicator instead of a complex system for detecting drowsiness.

Single indicator drowsy driving detection systems can include psychophysiological metrics or vehicle behavior metrics. Studies have shown that the use of a single indicator based on a driver psychophysiological activity – including monitoring driver eye movements and blinking (PERCLOS), electroencephalogram (EEG) of alpha and theta wave activity, electromyogram (EMG) of muscle activity correlated with alertness, electrocardiogram (EKG) monitoring of changes in heart rate variability associated with alertness, as well as several others – may not be a solution (Kecklund and Åkerstedt, 1993; Sandberg et al., 2011b; Vitabile et al., 2011). Generally speaking, drowsiness detection through biometrics is difficult, prone to error, have been shown to have low accuracy and robustness, and can be intrusive by interfering with the normal execution of actions (Shuyan and Gangtie, 2009). Thus, monitoring vehicle behavior and variability is perhaps the most logical and reliable form of drowsy driver detection for an effective single indicator; as well as the most practical for automotive manufacturers.

The most commonly used indicators for a vehicle behavior metric are measures of vehicle movement variability on the road – lateral lane position, steering wheel angle and reversal rates, and lane crossings (Forsman et al., 2013; Liu et al., 2009; Sandberg et al., 2011a; Wierwille et al., 1994). Another related measure less often seen in the literature, but shown to be one of the most sensative behavioral metrics for a single sleepiness indicator is difference in vehicle heading – also refered to as *yaw* (Sandberg et al., 2011a). However, a difference heading metics has an inharently high varability due to the nature of constant adjustments to the steering wheel to stay on course, and further consideration as to its statistical analysis needs to be considered.

Researchers agree future studies should focus on improving promising indicators of vehicle movement variability to be more sensitive to variability at lower levels of drowsiness (Liu et al., 2009). New systems should detect drowsy driving before driving is too risky. Because variability in vehicle heading has been shown to have a strong correlation with both psychophysiological and vehicle behavioral methods of detecting drowsiness; it is an ideal candidate for further exploration (Wierwille et al., 1994).

The purpose of this study is to improve on current drowsy driving technology by proposing a better-quality single indicator of driving error around curves that can be applied to reduce potential accidents. Research suggests that variability of vehicle heading difference is a nonintrusive and reliable method of monitoring driving behavior (Sandberg et al., 2011a). An alternative model is proposed as a superior single indicator by utilizing variability of vehicle heading difference, a promising and under-researched vehicle behavior metric, along with an absolute value of raw data method to account for overt variability. We hypothesize that using the absolute value of raw data method in combination with the vehicle heading difference metric will be a more effective single indicator of early onset drowsiness compared to other vehicle-based models. We also expect a significant change in psychomotor measures indicative of impairment due to drowsiness. Specifically, we expect an increase in reaction time, a decrease in attention, and an increase in oculomotor fatigue; three components which individually contribute to safe driving by allowing for accurate perception of and response to environmental cues.

2. Methods

2.1. Participants

A sample of twenty volunteers (11 females and 9 males) with a mean age of 20.55 (SD = 2.44) participated in the study. Participants were screened to ensure they were in good health, did not report excessively using drugs or alcohol as compared to other college students, did not use tobacco products, and had no history of seizures or sleep disorders. Subjects were not professional drivers, and received monetary compensation for their participation over two days. The Institutional Review Board of Clemson University approved the study design and all participants completed an informed consent form prior to the start of the study.

2.2. Experimental procedure

Participants used a sleep log to record their sleep times the three days prior to the laboratory measures. The night before the study, participants were instructed to sleep for eight hours and were called by a researcher on the morning of the study between 8:00 and 10:00 a.m. at a prearranged time to ensure they were awake. The participants reported to the research lab by 4:30 p.m. on the day of the study, where they remained until 11:00 a.m. the following morning, resulting in approximately 26 h of sleep deprivation. The participants were supervised throughout the night to ensure they remained awake and did not consume any alcohol or caffeine. Participants completed the study in groups of four, and were provided food choices without excessive sugar (e.g., sandwiches, fruit) and non-caffeinated beverages (e.g., water, decaffeinated tea) for the duration of the study.

Each participant completed a training session for each task. The training session was completed from 4:30 to 7:30 p.m. The training procedures for each task are described below in the description for each task. Following the training session, participants completed the five testing sessions. The testing sessions were completed from 8:00 to 10:30 p.m., 10:45 p.m. to 1:15 a.m., 1:45 to 4:15 a.m., 4:30 to 7:00 a.m., and 7:30 to 10:00 a.m. Participants completed several tasks previously reported to assess cognitive performance during sleep deprivation (Pilcher et al., 2007). The current analyses focused on three measures: a vigilance task to measure fatigue through reaction time (Jung et al., 2011; McClelland and Pilcher, 2007), an oculomotor fatigue task to measure drowsiness from voluntary eye movement delay (McClelland et al., 2010), and a high-fidelity driving simulator to measure driving performance (Broughton et al., 2007). Additional tasks in the study indexed cognitive, vigilance, and subjective performance measures. All tasks were counterbalanced between participants to remove task ordering effects.

2.3. Sleep log

Participants used a self-estimated sleep log to record time spent sleeping, awake, and being active for the three days prior to the night of sleep deprivation. Sleep logs were used to assess the persons sleep/wake cycles prior to the laboratory measures and determine whether they were sleep deprived prior to the study, and how long they had been awake on the night of the laboratory measures.

2.4. Driving task

Participants drove a KQ-Vection fixed-base, high-fidelity automotive driving simulator. The simulator was an accurately calibrated Mitsubishi Galant sedan cabin, utilizing DriveSafety HyperDrive software with fully functioning controls, instrumentation, and simulated road vibration with 3D sound. A four channel projection system displayed a 200° (four screens at 50°) horizontal field of view environment.

For all sessions, the simulated track depicted a daytime driving scenario with light fog and a flat rural landscape. The scenario included vertical road signage, but did not present stop-signs, traffic lights, or additional cars. The track was composed of eleven straight segments ranging from 200 m to 6800 m in length, and ten curved segments (90°; four rights and six lefts) at 150 m in length. Participants were asked to drive as they normally would, and to obey all signage and traffic laws. Each driving session took approximately 20 min to complete, with the speed limit signage at 55 mph. The simulator recorded 37 dynamic parameters; including lane position and vehicle heading, and logged data at a rate of 1 Hz.

2.5. Driving measures

The present study focused on driving behavior through curves. The first four curves of the track as well as the last two curves of the track were excluded from the analysis to ensure that participants were acclimated to the task for each session and to minimize any potential end-of-session effects. Performance measures for the driving task included variability of lateral lane position, one of the most commonly used driving metrics for indicating drowsiness through vehicle behavior; as well as variability of vehicle heading difference, a less common metric being explored as an alternative to lateral lane position (Forsman et al., 2013; Liu et al., 2009; Sandberg et al., 2011b; Wierwille et al., 1994).

The vehicle heading difference metric indexed the momentary difference between the direction of the participant's vehicle in degrees and the tangential direction of the lane in degrees (i.e., how much to the right or left the vehicle is facing at a particular instant relative to the lane). The heading difference metric was chosen because it took into account driving performance based on the direction of travel without the biased effects of variability from the lateral location. In contrast, the lateral lane position metric indexed the momentary distance in meters of the vehicle's center line from the lane's center line. For example a driver's tendency to drive high then low in the lane through a curve, keeping the steering wheel at a single position, would yield high lateral lane position variability with low heading difference variability. Likewise, a driver that made dramatic adjustments in the steering wheel, but maintained the vehicles position in the center of the lane, would yield low lateral lane position variability with high heading difference variability. Due to these related but intrinsic differences, the two metrics measuring variability would yield differences in variability, allowing for a performance comparison. Drivers could have high heading difference variability with low lateral lane variability and vice-versa.

The training session for the driving simulator task occurred in two parts. During the first part, participants sat in the simulator and had the functional controls and operations described to them. During the second part, participants received driving instruction and drove for an acclimation period prior to each of the five testing session. The instruction and acclimation period required the participant to drive the first four straight and curved sections of the track, taking approximately five minutes. The driving task was completed once during each testing sessions and took approximately 20 minutes to complete.

2.6. Psychomotor vigilance task (PVT)

The psychomotor vigilance task (PVT; Ambulatory Monitoring Inc., Ardsley, NY) provided a short duration vigilance and reaction time task using a portable device. The PVT has been shown to be sensitive to the fatiguing effects of sleep deprivation and does not show a learning curve (Dinges and Powell, 1985). Participants held the device and pressed a response button as soon as the device displayed a visual signal, while the device recorded the delay as time elapsed in milliseconds. Participants became acclimated with the device by completing a 5 min training demo during the training session. The demo was a truncated version of the typical testing session for the PVT. The PVT was administered once during each testing session and took approximately 10 min to complete.

2.7. Oculomotor fatigue measures (FIT)

The fitness impairment tester (FIT; PMI Inc., Rockville, MD) for the oculomotor fatigue measures task identified central nervous system changes and fatigue due to drowsiness by examining the reactions of the eye to control stimuli (Russo et al., 2003). The FIT machine measured eye saccade velocity (mm/s) as the participant followed a blinking light with their eyes while looking through a lens. Participants became acclimated with how the machine worked during two practice trials and six baseline measurements during the training session. The 30 s training sessions were identical to the real task. Each participant completed the FIT task twice before each testing session and twice after each testing session, with five minute breaks between each consecutive administration. Each administration of the FIT task lasted approximately 30 s.

3. Theory/calculation

3.1. Sleep log analysis

The primary sleep log measure used in this study was the time going to bed with the intention of sleeping, time asleep, and time getting out of bed. The participants completed the sleep logs immediately after awakening each morning. The sleep log data were analyzed to estimate time asleep during the three nights prior to the study.

3.2. Driving performance analysis

The primary driving performance measures recorded from the simulator were lateral lane position, lane heading, and vehicle heading. The vehicle heading difference was calculated using the lane heading and the vehicle heading measures. These metrics were extracted from four different periods of driving on the track, once from each of the four curves during each testing session. The number of samples collected per participant varied according to the participant's driving speed. To determine the amount of driving error, statistical variability of vehicle heading difference and lane position data was calculated using two methods. The first method used the absolute values of the raw data before calculating variability while the second method used the raw data to calculate variability. The use of absolute values in the first method allowed us to calculate the deviation without concern for the direction of the deviation from the perfect geometric turn while the second method using the raw data accounted for the direction of deviation.

To calculate the results for lateral lane position using the first method (Formula (1) below), lane position data in meters ($|X|$) was used for each second of a driven curve as an absolute value. To calculate the results for lateral lane position using the second method (Formula (2) below), lane position data in meters (X) was used as a raw value. To calculate the results for vehicle heading difference using the first method (Formula (1) below), lane heading data in degrees was subtracted from the absolute value of the vehicle heading data in degrees to get a vehicle heading difference ($|X|$) for each second of a driven curve. To calculate the results for vehicle heading difference using the second method (Formula (2) below), lane heading data in degrees was subtracted from the raw vehicle heading data in degrees to get a vehicle heading difference (X). Applying the two formulas to the two driving metrics (lane position and heading difference), resulted in four predictive models: Model 1–Formula (1) with lane position, Model 2–Formula (1) with heading difference, (The root mean square error from absolute difference formula used in the first method of data analysis.) Model 3–Formula (2) with lane position, and Model 4–Formula (2) with heading difference. (The standard deviation formula used in the second method of data analysis.)

$$\sqrt{\frac{\sum(|X| - \bar{x})^2}{N - 1}} \tag{1}$$

$$\sqrt{\sum\frac{(X - \bar{x})^2}{N - 1}} \tag{2}$$

Data were collected for a total of 400 driven curves (20 participants X 5 testing sessions X 4 curves) and were analyzed using the four models. Both lane deviation and vehicle heading difference were analyzed with a repeated-measures analysis of variance (ANOVA) using the IBM SPSS statistical program (SPSS 21; SPSS Inc., Chicago, IL). Results of the pairwise comparison were also used to show the significant difference of the variability between sessions for each model. If any model was sensitive enough to detect differences in variability between each session, it would have a total of ten significant differences. Results from the Greenhouse–Geisser test were reported, as the results from Mauchly's test of Sphericity were not significantly violated using either method. Since Sphericity was not violated, there is not a risk of inflated Type 1 error rates due to heteroscedasticity, and an adjusted multivariate F Test was not needed. Cohen's unbiased f was reported as an additional measure of effect size by analyzing the standardized average effect across all sessions. Cohen's f has been used and suggested as a more appropriate test by Cohen because it indexes the degree of departure from no effect as a pure number (Cohen, 1988).

3.3. Fatigue measures analysis

The primary performance measure for the PVT task was reaction time recorded in milliseconds. The reaction time data was collected from the participant during each of the five testing sessions, and then transformed in a spreadsheet using the inverse function. The inverse transformation was used to encourage normality by removing kurtosis and developing a predictive trend (Fink, 2009). The inverse reaction times in seconds were then averaged for each session and participant. The reaction time data was also analyzed for reaction time lapses, defined as cases where the individual's response took longer than 500 milliseconds, and indicated a loss of attention. The reaction time lapses in number of occurrences were also averaged for each session and participant.

The primary performance measure for the FIT task was eye saccade velocity recorded in millimeters per second at a sample rate of 750 Hz. The two readings taken before the driving task were averaged (denoted by *a* and *b*), as were the two readings taken after the driving task (denoted by an *a*) to get ten average readings across the five sessions for eye saccade velocity (i.e., 1*b*, 1*a*; 2*b*, 2*a*; 3*b*, 3*a*; 4*b*, 4*a*; 5*b*, 5*a*). These eye movement velocity data were then averaged for each session and participant.

PVT and FIT data were also analyzed with a repeated-measures ANOVA using the time period of the testing sessions as a factor. Results from Wilks' Lambda multivariate test were reported, as the results from Mauchly's test of Sphericity were significantly violated using both methods.

4. Results

4.1. Sleep log

Participants were well-rested on the day they reported to the lab. The self-estimated sleep log showed that participants slept an average of 7 h and 24 min (SD = 1 h and 17 min) across the three days, and 7 h 52 min (SD = 0 h and 34 min) the night before the laboratory measurements.

4.2. Driving performance indices

4.2.1. Deviation of lateral lane position

Performance on the driving task significantly decreased across the night using the deviation of lateral lane position metric with Formulae (1) and (2) methods. The decrease in performance is represented by an increase in variability across the night. Better error detection by a model is represented by a larger variability when comparing to the last session (positive slope) (Figs. 1 and 2).

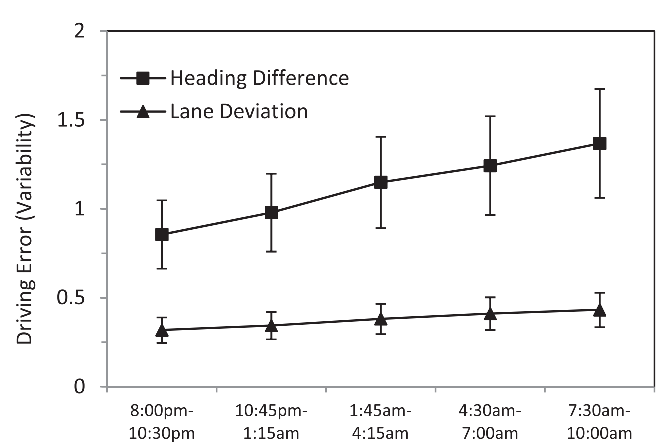

Fig. 1. Driving variability (error) over the night using Formula (1) method for lane deviation and heading difference (Mean ± Standard Error).

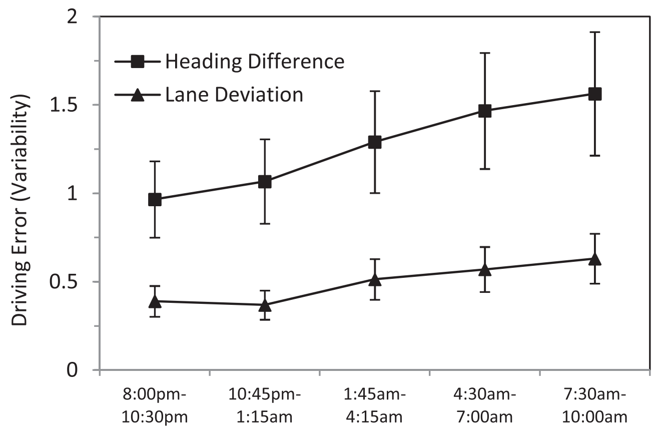

Fig. 2. Driving variability (error) over the night using Formula (2) method for lane deviation and heading difference (Mean ± Standard Error).

Better error detection is represented by a larger number of significant differences between sessions ($p < .05$); ranging from 0 (no driving performance differences were detected between sessions) to 10 (driving performance differences were detected between each of the five sessions) (Table 1). The performance of each model is assessed by comparing differences in driving variability between sessions (i.e., *F*-ratio, effect size), and organized by method and metric. Better error detection by a model is represented by a larger *F*-ratio and larger effect size (Table 2).

4.2.1.1. Formula 1. The repeated-measures ANOVA showed a significant increase in driving variability using Model 1 [F (4,76) = 10.011, $p < .001$, $\eta_p{}^2 = .345$]. The means comparison indicated that Model 1 also detected significant differences in driving performance between 6 of the 10 session comparisons (Table 1). Cohen's unbiased f for average effects showed a large effect size using the Formula (1) method [$f = 0.600$ ($\eta^2 = .264$)] (Cohen, 1988).

4.2.1.2. Formula 2. The repeated-measures ANOVA also indicated significant increases in driving variability using Model 3 [F (4,76) = 14.951, $p < .001$, $\eta_p{}^2 = .440$]. The means comparison indicated that Model 3 detected significant differences in driving performance between 7 of the 10 session comparisons (Table 1). Cohen's unbiased f for average effect across the samples also showed a large effect size using the Formula (2) method [$f = 0.747$ ($\eta^2 = .358$)].

4.2.2. Deviation of vehicle heading difference

Performance on the driving task significantly decreased across the night using the vehicle heading difference metric with Formulae (1) and (2) methods (Figs. 1 and 2; Tables 1 and 2).

4.2.2.1. Formula 1. The repeated-measures ANOVA showed a significant increase in driving variability using Model 2 [F (4,76) = 15.989, $p < .001$, $\eta_p{}^2 = .457$]. The means comparison indicated that Model 2 also detected significant differences in driving performance between 8 of the 10 session comparisons (Table 1). Cohen's unbiased f for average effects showed a large effect size using the Formula (1) method [$f = 0.77$ ($\eta^2 = .374$)].

4.2.2.2. Formula 2. The ANOVA also showed significant increases in driving variability using Model 4 [F (4,76) = 12.966, $p < .001$, $\eta_p{}^2 = .406$]. The means comparison indicated that Model 4 detected significant differences in driving performance between 7 of the 10 session comparisons (Table 1). Cohen's unbiased f for average effect across the samples also showed a large effect size using the Formula (2) method [$f = 0.69$ ($\eta^2 = .323$)].

4.3. PVT scores

Reaction time and the number of lapses increased across the night (Figs. 3 and 4). The Wilks' Lambda showed a significant increase in inverse reaction time [Wilks' Lambda = .142, F (4,17) = 25.585, $p < .001$, $\eta_p{}^2 = .858$]. The Wilks' Lambda also showed a significant increase in the number of lapses in responding [Wilks' Lambda = .346, F (4,17) = 8.033, $p = .001$, $\eta_p{}^2 = .654$].

4.4. FIT scores

Eye saccade velocity decreased across the night (Fig. 5). The Wilks' Lambda showed a significant decrease in saccade velocity [Wilks' Lambda = .249, F (9,17) = 5.683, $p = .001$, $\eta_p{}^2 = .751$].

5. Discussion

The current results showed that the proposed model using the new Formula (1) statistical method with the vehicle heading difference metric (Model 2) better predicted driving variability due to drowsiness than conventional models; thus, supporting our first hypothesis. The greater effect sizes and pairwise comparison differences associated with Model 2 indicated more vehicle behavior error was detected around a curve than the other three models, showing its potential for future safety technology. There was a significant increase in vehicle behavior error across the night. Of the three less effective models, the new Formula (1) statistical method with the lateral lane position metric (Model 1) was found to be the least effective, indicating that the Formula (1) method may only be effective when paired with certain metrics. Such findings are in agreement with Sandberg et al. (2011a), who found lane heading to be a more effective performance measure than lane position. Though less effective, lane position still identified a significant difference in performance as the drivers become more fatigued due to sleep, supporting previous driving simulator

Table 1
The pairwise comparisons of variability between sessions (1–5), significant differences have been highlighted.

Sessions		Model 1	Model 2	Model 3	Model 4
1	2	Not sig	Not sig	Not sig	Not sig
	3	<.05	<.05	<.05	<.05
	4	<.05	<.05	<.05	<.05
	5	<.05	<.05	<.05	<.05
2	1	Not sig	Not sig	Not sig	Not sig
	3	Not sig	<.05	<.05	<.05
	4	<.05	<.05	<.05	<.05
	5	<.05	<.05	<.05	<.05
3	1	<.05	<.05	<.05	<.05
	2	Not sig	<.05	<.05	<.05
	4	Not sig	Not sig	Not sig	Not sig
	5	<.05	<.05	<.05	<.05
4	1	<.05	<.05	<.05	<.05
	2	<.05	<.05	<.05	<.05
	3	Not sig	Not sig	Not sig	Not sig
	5	Not sig	<.05	Not sig	Not sig
5	1	<.05	<.05	<.05	<.05
	2	<.05	<.05	<.05	<.05
	3	<.05	<.05	<.05	<.05
	4	Not sig	<.05	Not sig	Not sig

Table 2
Summary table of the results from the tests of variability for each model (1–4).

Model	Method	Metric	Measures of variability				
			Cohen's unbiased f	Cohen's f converted to η^2	Greenhouse–Geisser (F)	Greenhouse–Geisser (η^2)	Significant mean comparisons
1	Formula (1)	Lateral position	0.600	0.265	10.110	0.345	6 of 10
2	Formula (1)	Vehicle heading	0.774	0.374	15.989	0.457	8 of 10
3	Formula (2)	Lateral position	0.747	0.358	14.951	0.440	7 of 10
4	Formula (2)	Vehicle heading	0.691	0.323	12.966	0.406	7 of 10

research (Forsman et al., 2013; Liu et al., 2009; Wierwille et al., 1994).

As hypothesized, the increase in driving error occurred in conjunction with significant changes in psychomotor measures that are relevant to driving performance. Measures of fatigue using a reaction time task to measure vigilance and attention, and an oculomotor saccade task showed a decrease in participant performance throughout the night. These results support previous studies suggesting that fatigue due to extended periods of wakefulness can be indexed using button-based reaction time tasks and oculomotor measures (Jung et al., 2011; McClelland and Pilcher, 2007; McClelland et al., 2010). The PVT task showed a significant increase in reaction time across the night, and a significant increase in response lapses due to attentional deficit. The FIT task showed a significant decrease in eye saccade velocity across the night due to oculomotor fatigue from drowsiness which would impair environmental perception. The PVT and FIT results suggest that the participants in the current study experienced increasing drowsiness across the night of sleep deprivation which could have contributed to the driving error that was indicated by the four detection models.

Previous literature has shown that improved single drowsy driving indictors are needed for the development of better driving technology. As such, statistically viable models using single indicators are valuable additions to the current understanding of dangerous driving (Sandberg et al., 2011a). The use of a vehicle heading based metric is a promising single indicator of drowsy driving, though nearly absent in literature (Sandberg et al., 2011a). Heading metrics are also a nonintrusive approach to drowsy driving detection technology which overcomes one of the limitations in current drowsy driving detection technology (Liu et al., 2009; Wierwille et al., 1994). The current results indicated that the proposed single indicator based statistical models were sensitive and predictive of increased error in driver performance following increased drowsiness.

A crucial component of proposing a new analytical approach to drowsy driving detection is the potential for real world application and integrated safety systems. The foundational components of our new models merge previous detection techniques with a new statistical method, and demonstrate promising results. Each model uses retrospective analysis as opposed to real-time analysis, taking advantage of a holistic view of driving by analyzing the road segment in its entirety. This allows the proposed methodology to be used in conjunction with current real-time technology which only considers moment by moment metrics like lane crossings. Applications for the system may include providing the driver with a statistical driving score or graphic display to give feedback on their performance, encouraging self-awareness of drowsiness. The system may also be synced directly to an audio/visual warning system, and be used to alert the driver of dangerous behavior if overt variability is detected. Previous studies have shown that providing retrospective feedback to drivers on their driving performance resulted in fewer driving errors after the fact (Zhao and Wu, 2012).

In real world applications, the three primary components required for the functional implementation of the proposed methodology are lane heading data, vehicle heading data, and a system for analysis. Lane heading data can be gained using accurate differential global positioning system technology (DGPS) and can provide feedback to the system based on current vehicle location and direction (heading) of lane. Vehicle heading data can be gathered using onboard computers with a directional sensor (heading) based on the vehicles center line, and would provide feedback to the system based on current vehicle direction. Using this method, a system would use DGPS to detect when a vehicle was nearing a curve, and systematically sample the lane heading along with the current vehicle heading. Once the vehicle completed the curve, the system would run the statistical model. If the value (variability) was considered to be beyond a set cutoff, then a separate system for alerting the driver could be initiated.

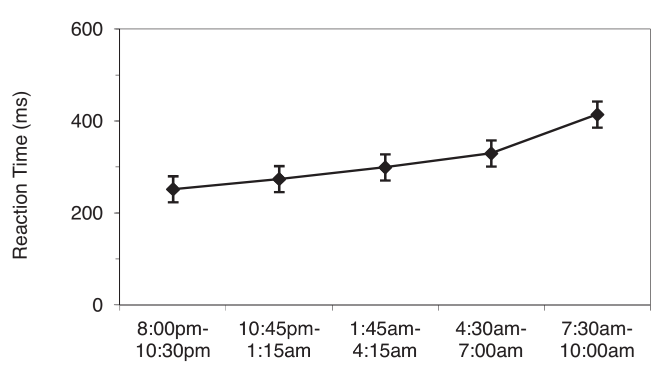

Fig. 3. Reaction time in milliseconds from PVT task after an inverse transformation (Mean ± Standard Error).

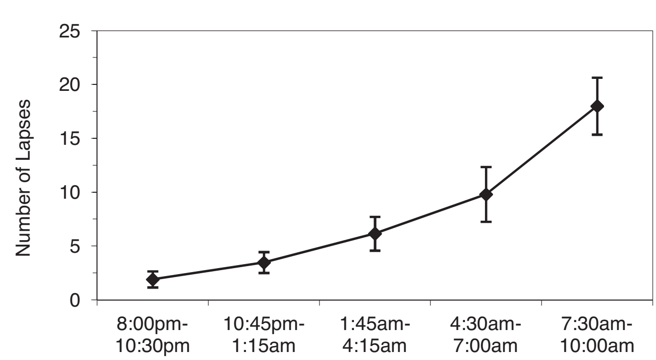

Fig. 4. Number of lapses (response time >500 ms) from PVT task (Mean ± Standard Error).

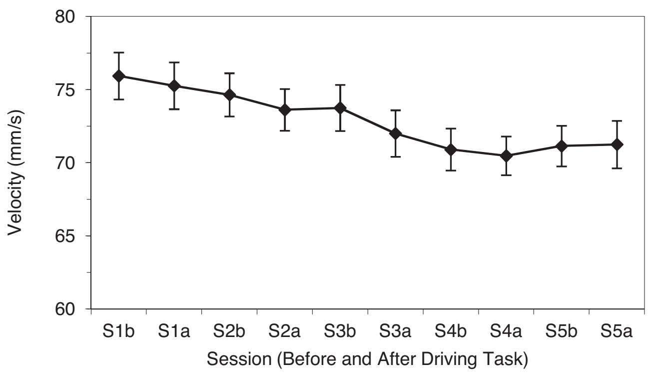

Fig. 5. Eye saccade velocity before (b) and after (a) each driving session (1–5) (Mean ± Standard Error).

Successful implementation of the drowsy driver detection methods supported in the current study requires additional research to fully understand its limitations and potential. There are several limitations in the current study. It is important to note that the driving error data was collected using a high-fidelity driving simulator and not an actual vehicle on an active road. The scenario did not incorporate traffic and used only a daytime environment with good visibility. Such an environment is common to drowsy driving literature, but may limit generalizability in high traffic environments. Participants were told to treat the task as if they were driving normally; however, the lack of real danger associated with driving error may still have influenced their performance. Since this may limit the generalizability of the findings, real world variables should be further explored before implementing any type of advanced vehicle safety system. Model 2 was successful at indexing driver error around curves, though further potential for its application on straight segments may exists. Another limitation was the use of college students as participants. Because the participants were all young, they do not represent a cross-section of all drivers. Future studies could use a wider range of participants to test the new metric being proposed here. A final limitation is the lack of a control group in the current study. To implement a true control group for a sleep deprivation study that examines performance during the sleep deprivation period, one would have to find volunteers who would invert their circadian rhythms so that they could complete the study at night but in a well-rested state, which would be very difficult to do. However, because the current study assessed performance multiple times during the night, we could make comparisons on changes in performance across the night. The current study design simulates someone driving throughout a night which commonly happens in modern society.

6. Conclusion

In summary, traffic accidents due to drowsiness could be reduced with the successful implementation of drowsy driving detection technology. Previous models and systems for this purpose have been developed, but may not be practical in real world application or do not detect driving variability as effectively as may be possible. Our proposed Model 2 builds on the best practices of previous research, and suggests a methodology of implementation by using statistical analysis around curves. Model 2 detected error in the presence of driver fatigue due to sleepiness, and may function as a predictor of drowsiness impairment accordingly. The methodology and findings from this study contribute to current literature by showing the potential for a single indicator of drowsy driving based on vehicle heading when analyzed using retrospective analysis.

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