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Efficient driver drowsiness detection at moderate levels of drowsiness

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ABSTRACT

Previous research on driver drowsiness detection has focused primarily on lane deviation metrics and high levels of fatigue. The present research sought to develop a method for detecting driver drowsiness at more moderate levels of fatigue, well before accident risk is imminent. Eighty-seven different driver drowsiness detection metrics proposed in the literature were evaluated in two simulated shift work studies with high-fidelity simulator driving in a controlled laboratory environment. Twenty-nine participants were subjected to a night shift condition, which resulted in moderate levels of fatigue; 12 participants were in a day shift condition, which served as control. Ten simulated work days in the study design each included four 30-min driving sessions, during which participants drove a standardized scenario of rural highways. Ten straight and uneventful road segments in each driving session were designated to extract the 87 different driving metrics being evaluated. The dimensionality of the overall data set across all participants, all driving sessions and all road segments was reduced with principal component analysis, which revealed that there were two dominant dimensions: measures of steering wheel variability and measures of lateral lane position variability. The latter correlated most with an independent measure of fatigue, namely performance on a psychomotor vigilance test administered prior to each drive. We replicated our findings across eight curved road segments used for validation in each driving session. Furthermore, we showed that lateral lane position variability could be derived from measured changes in steering wheel angle through a transfer function, reflecting how steering wheel movements change vehicle heading in accordance with the forces acting on the vehicle and the road. This is important given that traditional video-based lane tracking technology is prone to data loss when lane markers are missing, when weather conditions are bad, or in darkness. Our research findings indicated that steering wheel variability provides a basis for developing a cost-effective and easy-to-install alternative technology for in-vehicle driver drowsiness detection at moderate levels of fatigue.

1. Introduction

Drowsy driving (or driving while sleepy or fatigued) is a main contributor to road crashes (National Transportation Safety Board, 1999), as corroborated by various sources of data. In Europe, up to 20% of all traffic accidents are believed to be due to driver drowsiness (AWAKE, 2002). In the U.S., falling asleep while driving causes at least 100,000 crashes annually; 40,000 lead to nonfatal injuries, and over 1500 result in fatal injuries (Royal, 2002). As many as 28% of polled U.S. drivers admit to nodding off at the wheel at least once (National Sleep Foundation, 2009). In light of these disconcerting statistics, countermeasures against drowsy driving have received increased attention during the last couple of decades (Dinges et al., 1998).

To safeguard against drowsy driving, carmakers are developing technologies to monitor car-based metrics of driving performance and warn the driver of impending drowsiness. Such technologies typically rely on the detection of lane departures, large lateral deviations within the lane, and/or cessation of steering corrections (Galley et al., 2009; Seko et al., 1986; Victor, 2009). Whether these technologies truly serve a preventive purpose by detecting drowsiness sufficiently early on, without the help of physiological measures of sleepiness recorded from drivers themselves (see Vadeby et al., 2010), has not been convincingly demonstrated. In particular, there is an ongoing need to develop tools for reliably detecting driver drowsiness at relatively moderate levels of drowsiness, so that drowsy driver crashes can be anticipated and avoided well in advance.

In a literature search we found that researchers have tested at least 87 different metrics of driving performance for their potential

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usefulness in detecting driver drowsiness. The metrics we considered are described in Appendix A and are discussed in Berglund (2007), Boyle et al. (2008), Fagerberg (2004), King et al. (1998), Kircher et al. (2002), Mattsson (2007), Otmani et al. (2005), Pizza et al. (2008), Tijerina et al. (1999), and Wierwille et al. (1994). We found no published large-scale comparisons between the available metrics, but there are a few comparisons within subsets of selected metrics. Depending on the study, different metrics stand out as those potentially most sensitive to driver drowsiness. For example, Friedrichs and Yang (2010) compared 31 metrics of driving performance and found that among these metrics, the average steering angular velocity was the most sensitive. Sandberg et al. (2011a) compared 18 metrics and reported that variability of lateral velocity was the most sensitive. In a joint effort, Berglund (2007) and Mattsson (2007) compared a set of 17 metrics and found that a linear combination of steering wheel direction reversals, vehicle path deviations, and standard deviation of lateral position was most sensitive to driver drowsiness.

These examples illustrate that no consensus exists regarding which metric or combination of metrics would be the most sensitive to driver drowsiness. Moreover, given the multitude of available metrics, some degree of collinearity among them is to be expected. Using high-fidelity driving simulator data from drowsy participants and alert controls studied in a laboratory setting, we set out to examine collinearity among the 87 driving metrics we found in the literature. From this work, we were able to develop a new approach to detecting driver drowsiness at moderate levels of drowsiness, which is presented here.

2. Methods

We used data from two laboratory-based, high-fidelity driving simulator studies, referred to here as Study A (Van Dongen and Belenky, 2010; Van Dongen et al., 2011a) and Study B (Van Dongen et al., 2010). The design of these studies was very similar; they are therefore described together here.

2.1. Participants

The total dataset included data from $N = 41$ participants aged 22–39. Study A contributed 25 participants (mean age $\pm$ SD: 27.3 ± 5.5; 13 men, 12 women). Study B contributed 16 participants (mean age $\pm$ SD: 27.5 ± 5.6; all men).

Participant inclusion criteria were: good health (by physical examination, blood chemistry and questionnaires) and not a current smoker, good sleep (by baseline polysomnography, at-home actigraphy, at-home sleep diary and questionnaires), no shift work or transmeridian travel within one month of entering the study, valid driver's license, and not susceptible to simulator adaptation sickness (by structured, supervised test driving of the simulator). Participants gave written informed consent, and were compensated for their time. Both studies were approved by the Institutional Review Board of Washington State University.

2.2. Protocol

Both studies were strictly controlled laboratory studies. Participants lived inside the laboratory continuously for 14 days (Study A) or 16 days (Study B). In Study A, participants were randomized to either a night shift condition ($n = 13$) or a day shift condition ($n = 12$). Fig. 1 shows the schedules of the two conditions in Study A. In Study B, all participants were assigned to a night shift condition essentially equivalent to that of Study A.

In Study A, participants came to the laboratory at 09:00. The night shift condition began with a baseline day, which included three sessions, at 12:00, 15:00 and 18:00, to practice the test procedures (described below), and which contained nighttime sleep (time in bed (TIB): 22:00–08:00). Day two in the laboratory involved a nap opportunity (TIB: 15:00–20:00) to help transition to the night shift schedule. Participants where then subjected to 5 days of night shift, during which they had daytime sleep (TIB: 10:00–20:00) and took the performance tests (described below) at 21:00, 00:00, 03:00 and 06:00. After the 5-day shift work period, participants were given a 34-h restart break in the laboratory, which involved a break from testing and contained a nap opportunity (TIB: 10:00–15:00) to transition back to a daytime schedule, nighttime sleep (TIB: 22:00–08:00), and another nap opportunity (TIB: 15:00–20:00) to transition back to the night shift schedule. After the restart break, participants were subjected to another 5 days of night shift, identical to the first 5 days. The study ended with a nap opportunity (TIB: 10:00–15:00) to transition back to a daytime schedule, and a nighttime recovery sleep opportunity (TIB: 22:00–08:00). Participants left the laboratory at 14:00 on day 14. See Fig. 1 (top panel).

The day shift condition also began with a baseline day that included three sessions, at 12:00, 15:00 and 18:00, to practice the test procedures, and contained nighttime sleep (TIB: 22:00–08:00). Day two in the laboratory involved daytime wakefulness (no performance testing) and nighttime sleep (TIB: 22:00–08:00). Participants were then subjected to 5 days of day shift, during which they had nighttime sleep (TIB: 22:00–08:00) and took the performance tests at 09:00, 12:00, 15:00 and 18:00. After the 5-day shift work period, participants were given a 34-h restart break in the laboratory, which involved a break from testing and contained two nighttime sleep opportunities (TIB: 22:00–08:00). After the restart break, participants were subjected to another 5 days of day shift, identical to the first 5 days. The study ended with another nighttime sleep opportunity (TIB: 22:00–08:00), and participants left the laboratory at 14:00 on day 14. See Fig. 1 (bottom panel). Total TIB and the total number of performance tests were identical for the night shift and day shift conditions.

In Study B, there was only a night shift condition, which was equivalent to that of Study A – except that the baseline and restart periods were each a day longer, both adding a nighttime sleep period (TIB: 22:00–08:00) and a daytime waking period without testing. The total number of performance tests was identical to that in Study A.

2.3. Measurements

During the two 5-day shift periods, sessions with performance testing were scheduled four times per day (time points 1–4) – see Fig. 1. Each session included a 10-min psychomotor vigilance test (PVT; Dinges and Powell, 1985); a 30-min driving session on a high-fidelity driving simulator; another 10-min PVT; and a brief (less than 15-min) neurobehavioral test battery, which included computerized versions of the Karolinska Sleepiness Scale (KSS; Åkerstedt and Gillberg, 1990), a visual analog scale of mood (Monk, 1989), the Positive and Negative Affect Schedule (Watson et al., 1988), a digit-symbol substitution task (Wechsler, 1981), performance and effort rating scales (Dinges et al., 1992), and a cardinal direction decision task (Gunzelmann et al., 2004). Thus, each driving session was paired with independent, established indices of fatigue (e.g., Belenky et al., 2003; Van Dongen et al., 2003, 2011a). The laboratory accommodated four participants at a time, and there were two driving simulators. Therefore, participants were randomly assigned to consistently either do the driving, preceded and followed by the PVT, first and the neurobehavioral testing second, or the other way around. Either way, each session had a 45-min break between PVT/driving/PVT and the neurobehavioral test battery.

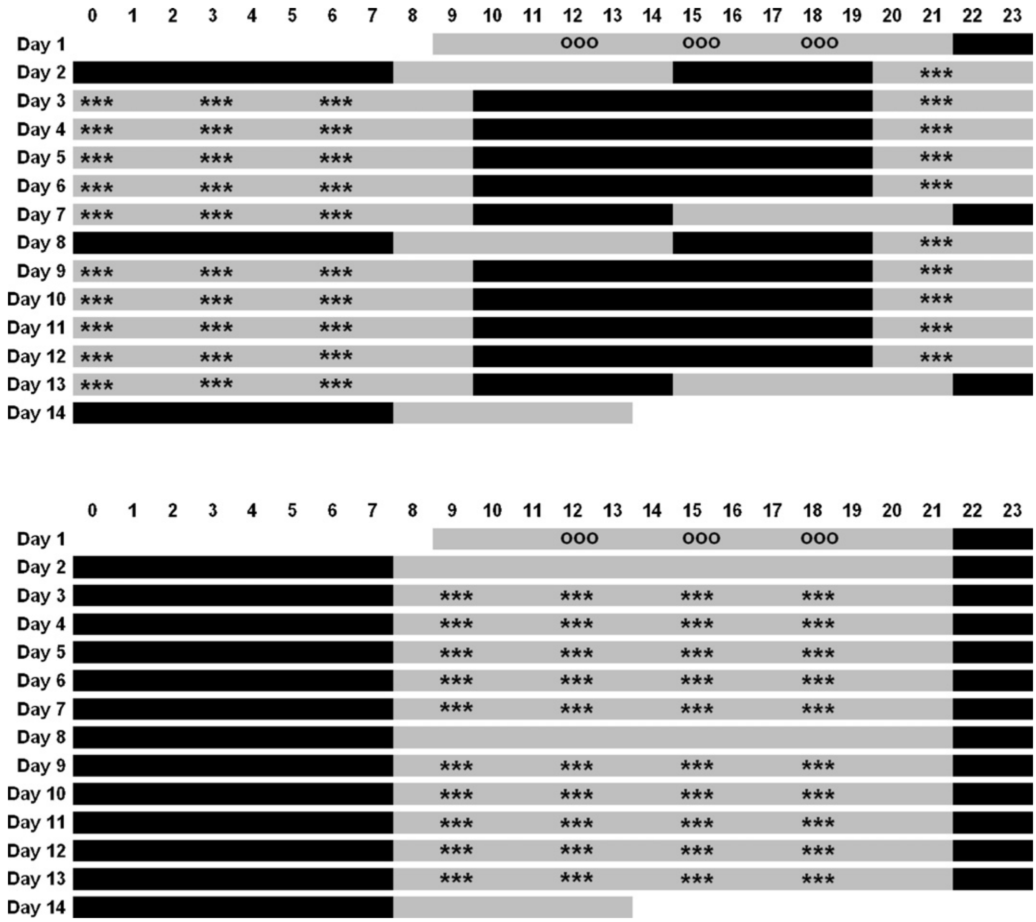

Fig. 1. Study protocol for the night shift condition (top) and the day shift condition (bottom) in Study A. Hours of the day (midnight to midnight) progress from left to right; days of the study progress from top to bottom. Gray marks scheduled wakefulness; black marks scheduled sleep. Triple asterisks denote 30-min driving simulator bouts, each preceded and followed by a 10-min psychomotor vigilance test (PVT) and each paired with a neurobehavioral test battery including the Karolinska Sleepiness Scale (KSS). Triple circles mark practice sessions. The protocol for Study B was equivalent to that of the night shift condition in Study A (top), except for an extra baseline day (added between days 1 and 2) and an extra restart day (added between days 7 and 8).

During every driving session, participants drove a simulated Ford Taurus in a fixed-base, high-fidelity driving simulator (PatrolSim IV, L-3 Communications) – see Fig. 2. The simulator was adapted for driving measurement purposes by installing additional hardware and software external to the simulator (Moore et al., 2009). The simulator proper uses both hardware and software to realistically simulate the mechanics and driving characteristics of an actual car. The processes relevant to understanding how changes in steering wheel position are translated into changes in vehicle heading within the simulator are realistically complex, and rely on a series of modeled vehicle components (personal communication, L-3 Communications, November 2011):

Fig. 2. High-fidelity driving simulator and driving track. Left: Stock image of the driving simulator, showing a test drive scenario (displays are full color). Right: Map of the simulated 28-mile driving track. The white segments mark the locations of the ten 0.5-mile straightaways along the track; the gray segments mark the locations of the eight 0.5-mile curve segments along the track. The driving direction was counter-clockwise.

- When the steering wheel is turned, an electric motor at the end of the steering shaft provides force feedback to the driver. This feedback realistically mimics the effects of power steering assistance, centering torques when the tires trail the steering axes, surface/tire interactions when the car runs over an object, and steering resistance when the steering wheel is maximally turned or when the car is stopped.
- Steering wheel position is converted by the simulator software into the Ackerman angles for each tire, while accounting for steering shaft compliance and the steering ratio of the simulated car make and model. Ackerman angles account for the different distances that the tires on the inside and the outside of a turn need to roll, and steering ratio accounts for the relationship between rotation of the steering wheel and the change in the angular direction of the tires.
- Steering hub headings are computed while accounting for the Ackerman angles, the toe angles, and suspension induced

steering. The toe angle is the symmetric angle that each tire makes with the vehicle heading. In suspension-induced steering, the vertical travel of the suspension alters the steering angles of the tires.

- Road surface forces are simulated by computing the interactions by which the forces from the simulated chassis and drive train act on the road surface – and the forces from the road surface act back on the suspension and chassis – thereby determining the chassis heading. The surface/tire model accounts for the friction coefficient between the tires and the surface, the lateral and longitudinal slip angles, and the speed, direction, and mass of the car, yielding a realistic account of the relationship between steering wheel movement and vehicle heading.

We employed a standardized driving scenario, which involved driving in daylight with clear view on a rural highway with no wind and without other vehicles. At fixed locations along the 28-mile track were ten 0.5-mile *straight* and uneventful road segments ("straightaways") and eight 0.5-mile *curved* and uneventful road segments ("curves") – see Fig. 2. At five to seven random other locations along the track were encounters with dogs or pedestrians crossing the road. The posted speed limit participants were instructed to maintain was 55 mph, and completing the drive took about 30 min. Simulated vehicle data (speed, acceleration, steering wheel angle, heading, etc.) were sampled at 72 Hz (Study A) or 60 Hz (Study B).

Each driving session was preceded and followed by a 10-min PVT. The PVT is a simple reaction time task with high stimulus density, which measures sustained attention (Lim and Dinges, 2008). The primary outcome metric was the number of lapses, defined as reaction times longer than 500 ms. For the present data analyses we considered lapses in the pre-driving PVT only. By design (Van Dongen et al., 2011a), PVT lapses served as the primary independent measure of fatigue. As a secondary independent measure of fatigue, we considered the KSS, on which participants rated their subjective sleepiness from 1 (very alert) to 9 (very sleepy).

Participants practiced the simulator driving and the various performance tests three times during the baseline period. The data from these practice sessions were not used. There were, therefore, 40 sessions for analysis (i.e., 4 sessions per shift day times 5 days per shift work period times 2 shift work periods) during Study A (both conditions) as well as Study B. For one participant in Study A, data from 25 out of the 40 sessions were missing.

2.4. Data analysis

For every driving session, primary signals (lane position, steering wheel angle, driving speed, accelerator usage, car yaw angle, engine torque) were extracted from each 0.5-mile straightaway. The signals of the ten straightaways were concatenated to form consolidated 5-mile time series for every driving session. The number of samples in the time series varied according to the sampling rate (72 or 60 Hz) and the participants' driving speed (which varied slightly around the speed limit of 55 mph). In Study A, the number of data points per time series (mean $\pm$ SD) was $22{,}660 \pm 315$; in Study B, it was $18{,}540 \pm 610$. For each time series, we computed the 87 driving metrics described in Table A.1 in Appendix A. The resulting datasets consisted of 87,000 data cells (25 participants times 40 driving sessions times 87 metrics) for Study A and 55,680 data cells (16 participants times 40 driving sessions times 87 metrics) for Study B.

To reduce the dimensionality of these large datasets, we performed principal component analysis (PCA) with orthogonal varimax rotation. We inspected the scree plots of eigenvalues and identified breaks (bends) in the plots to determine how many dimensions to retain before rotation in order to parsimoniously explain most of the variance in the data. This was done for Studies A and B separately to verify stability of the results. We focused on factor loadings with an absolute value of 0.5 or greater and retained components that were populated by more than two metrics displaying such high factor loadings and sharing the same conceptual meaning (Hatcher, 1994).

Previously published analyses of global performance outcomes in Study A (Van Dongen et al., 2011a) indicated increasing fatigue across time points in the work periods of the night shift condition, but not in the day shift condition. We utilized this feature of the study design to examine variables' sensitivity to fatigue. For Study A, we performed mixed-effects analysis of variance (ANOVA) with shift type (night vs. day) and time points (1–4) as fixed effects, and participants as random effect on the intercept (see Van Dongen et al., 2004b). For Study B, we performed mixed-effects ANOVA with time points (1–4) as fixed effect, and participants as random effect on the intercept. We included participants' assignment to simulator (#1 or #2) as a covariate, to control for any potential hardware differences.

To compare variables, we assessed correlations between time series while accounting for between-subject variance (Bland and Altman, 1995) in Study A (separately for the night shift condition and for the day shift condition) and in Study B (separately from Study A). As between-subjects variance in the impact of fatigue tends to differ from one measure of fatigue to another (Van Dongen et al., 2011b) and may therefore confound these correlations, we also computed group-average correlations, that is, correlations between time series averaged over the participants in each group (i.e., in Study A separately for the night and day shift conditions and in Study B).

PCA results prompted us to examine the relationship between steering wheel movements and lateral lane position changes. We derived the transfer function (Saul et al., 1991) between steering wheel angle and lateral lane position for the simulators over all 10,000 straightaways in Study A (i.e., 10 straightaways per bout times 40 bouts per participant times 25 participants) and all 6400 straightaways in Study B (i.e., 10 straightaways per bout times 40 bouts per participant times 16 participants), while differentiating between the two driving simulators in the laboratory to account for any potential hardware differences. The hardware of simulator #2 was serviced, and software settings (including sampling rate) were changed, between Studies A and B; we therefore derived the transfer functions separately for the two studies. Using the transfer functions, we estimated relative changes in lane position based solely on the sampled steering wheel angle, and then used the estimated changes in lane position to recalculate the lane position-based metrics defined in Appendix A.

We also examined whether straightaway results generalized to curves. To remove relatively slow, deliberate steering movements arising from navigating the road curvature, we applied a second-order high-pass filter (Brian and Barr, 2002) with a cut-off frequency of 0.011 Hz to all signals recorded from the eight 0.5-mile curves. After filtering, we computed the 87 driving metrics in Appendix A for each of the eight 0.5-mile curves, and averaged every metric across the eight curves within each driving session. We also used the factor loadings for the dimensions derived with PCA from the straightaway datasets to compute factor scores for the curves (Suhr, 2005). From there on, we performed the same analyses as for the straightaways. We also correlated the curve-based metrics with the straightaway-based metrics using the correlation procedure described above.

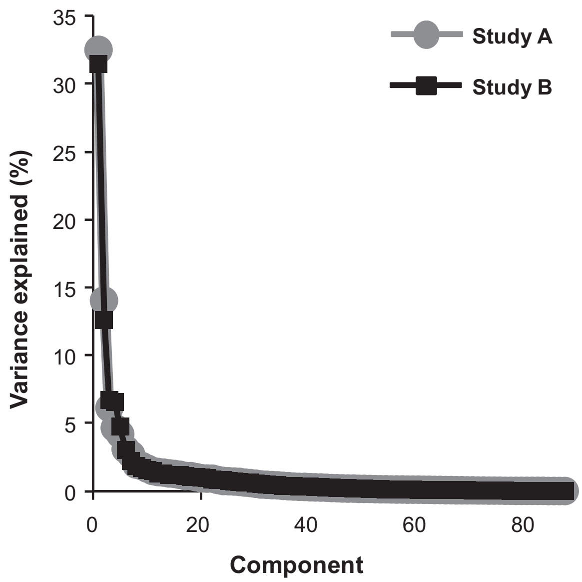

Fig. 3. Scree plot of eigenvalues expressed in terms of variance explained.

3. Results

3.1. Dimensionality of the 87 driving metrics

The scree plots of eigenvalues for the PCAs that we used to reduce the dimensionality of the 87 available driving metrics in Studies A and B consistently showed a break after the second component (see Fig. 3). This indicated that there were two dominant dimensions, which together explained 47% (Study A) and 44% (Study B) of the total variance in the driving datasets. Dimension 1 explained 33% (Study A) and 31% (Study B) of the variance; dimension 2 explained 14% (Study A) and 13% (Study B) of the variance.

The first dimension displayed high factor loadings for metrics capturing steering variability (see Table 1), and is therefore referred to as *steering variability* hereafter. The proportion of steering wheel movements exceeding three degrees in angle ($STEX_3(S)$, defined in Appendix A) had the highest loading on this dimension in Study A. The standard deviation of angular velocity of the steering wheel ($SD(AV)$, defined in Appendix A) had the highest loading on this dimension in Study B, but $STEX_3(S)$ also had a high loading.

Table 1
PCA results: factor loadings after orthogonal varimax rotation. Only metrics exhibiting factor loadings with an absolute value of 0.5 or greater (italicized) on at least one of the two dominant dimensions are shown.

Metric[a]	Study A		Study B	
	Dimension 1	Dimension 2	Dimension 1	Dimension 2
$STEX_3(S)$	*0.950*	−0.050	*0.939*	−0.090
$PHASE_{arc}(S)$	*0.949*	−0.086	*0.940*	−0.216
$DEV_{mean}(S)$	*0.949*	0.074	*0.927*	0.178
$DEV(S)$	*0.948*	0.063	*0.931*	0.161
$SD(AV)$	*0.945*	0.067	*0.949*	−0.157
$RMS(AV)$	*0.944*	0.067	*0.947*	−0.156
$DEV_{var}(S)$	*0.917*	0.076	*0.895*	0.127
$PHASE_{area}(S)$	*0.883*	0.048	*0.899*	−0.097
$E(S)$	*0.863*	0.026	*0.913*	−0.077
$VAR(AV)$	*0.790*	−0.065	*0.635*	−0.017
$SD(L)$	0.049	*0.914*	−0.129	*0.849*
$DEV_{mean}(L)$	0.030	*0.909*	−0.142	*0.845*
$DEV(L)$	0.020	*0.902*	−0.102	*0.782*
$DEV_{var}(L)$	0.015	*0.856*	−0.117	*0.815*
$VAR(L)$	0.011	*0.843*	−0.094	*0.786*

[a] Acronyms are defined in Appendix A.

The second dimension exhibited high factor loadings on metrics capturing variability in lateral lane position (see Table 1), and is therefore referred to as *lane variability* hereafter. The standard deviation of lateral lane position ("$SD(L)$", defined in Appendix A) had the highest loading on this dimension in Studies A and B.

The finding that the dimension *steering variability* explained more variance than the dimension *lane variability* could be a mere consequence of the fact that there were more steering-related metrics (45) than lane position-related metrics (20) in the datasets. To examine this, we performed a secondary PCA with equal numbers of steering-, lane-, and speed-related metrics (steering: $SD(S)$, $VAR(S)$, $RMS(S)$, $MEAN(S)$, $SD(AV)$, $VAR(AV)$, $RMS(AV)$, $MEAN(AV)$; lane: $SD(L)$, $VAR(L)$, $RMS(L)$, $MEAN(L)$, $SD(LV)$, $VAR(LV)$, $RMS(LV)$, $MEAN(LV)$; and speed: $SD(S)$, $VAR(S)$, $RMS(S)$, $MEAN(S)$, $SD(A)$, $VAR(A)$, $RMS(A)$, $MEAN(A)$ – see Table A.1 in Appendix A for metrics descriptions).

The scree plots again showed breaks after the second component, revealing that there were still two dominant dimensions, which together explained 47% (Study A) and 49% (Study B) of the total variance. Steering-related metrics again clustered on the first dimension, which explained 32% (Study A) and 30% (Study B) of the variance, and lane position-related metrics clustered on the second dimension, which explained 15% (Study A) and 19% (Study B) of the variance, confirming the dominance of the steering-related metrics regardless of their number.

These results show that among the 87 different metrics of driving performance drawn from the literature, in the two studies there were only two distinct major components of variance, reflecting *steering variability* and *lane variability*.

3.2. Fatigue changes over time of day

For Study A, mixed-effects ANOVA of the factor scores of *steering variability* revealed a significant effect of time point ($F_{3,940} = 3.05$, $P = 0.027$) and a significant interaction of condition by time point ($F_{3,940} = 3.75$, $P = 0.011$). The *steering variability* factor scores increased toward the end of the night shift (especially during the first shift period), but decreased toward the end of the day shift (Fig. 4, top left). The same pattern was seen for $STEX_3(S)$, the percentage of steering movements exceeding 3° (see Appendix A), which was the most representative metric (highest factor loading) for the *steering variability* dimension. For $STEX_3(S)$ there was an effect of time point ($F_{3,940} = 2.30$, $P = 0.075$) and a significant interaction of condition by time point ($F_{3,940} = 4.32$, $P = 0.005$).

For *lane variability*, there was likewise a significant effect of time point ($F_{3,940} = 12.1$, $P < 0.001$) and a significant interaction of condition by time point ($F_{3,940} = 4.30$, $P = 0.005$). The *lane variability* factor scores increased more toward the end of the night shift than toward the end of the day shift (Fig. 4, middle left). There was also a practice effect in the *lane variability* dimension, with performance improving from before to after the restart break (cf. Van Dongen et al., 2011a). The same pattern was seen for $SD(L)$, the standard deviation of lateral lane position (see Appendix A), the most representative metric (highest factor loading) for the *lane variability* dimension. For $SD(L)$ there was a significant effect of time point ($F_{3,940} = 8.40$, $P < 0.001$) and a significant interaction of condition by time point ($F_{3,940} = 5.35$, $P = 0.001$).

Mixed-effects ANOVA of PVT lapses revealed a significant effect of time point ($F_{3,940} = 9.20$, $P < 0.001$) and a significant interaction of condition by time point ($F_{3,940} = 5.94$, $P < 0.001$). For KSS sleepiness there was a significant effect of time point ($F_{3,940} = 60.4$, $P < 0.001$) and a significant interaction of condition by time point ($F_{3,940} = 42.8$, $P < 0.001$). The number of PVT lapses (Fig. 4, top right) and the KSS sleepiness score (Fig. 4, middle right) increased across time points in the night shift condition but not in the day shift condition.

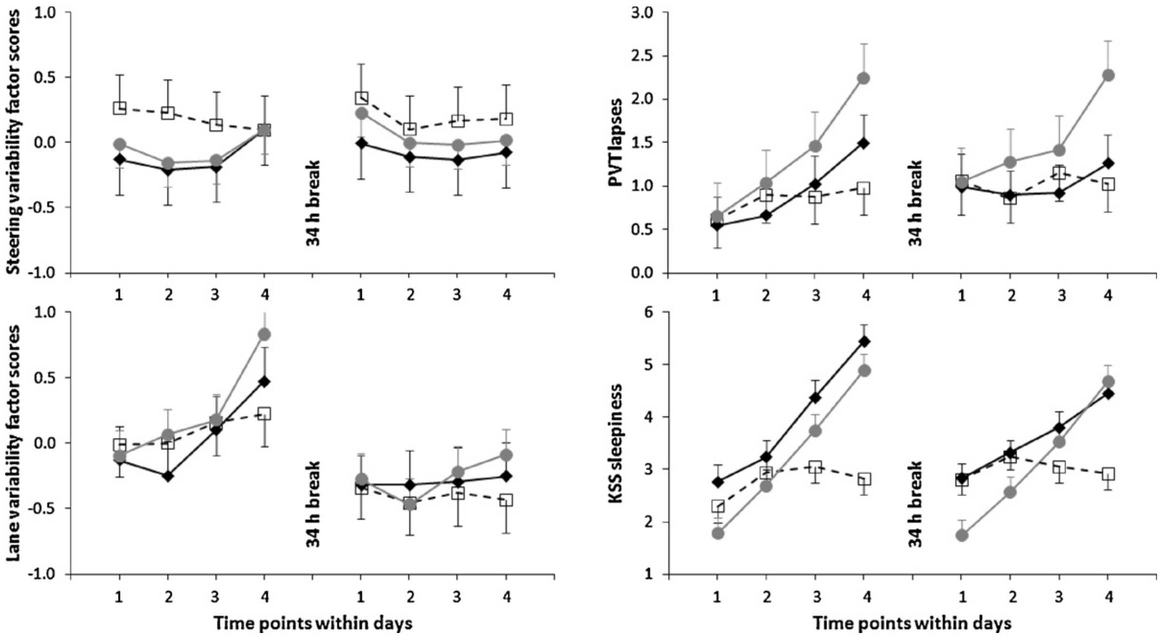

Fig. 4. Performance in the night shift condition (black diamonds, solid lines) and the day shift condition (white boxes, dashed lines) in Study A, and in the night shift condition (gray circles, gray lines) in Study B. The panels show group means and standard errors by time of day, collapsed over days, for the two 5-day shift periods in the study separated by the 34-h restart break, as derived from mixed-effects ANOVA. Time points were 21:00, 00:00, 03:00 and 06:00 for night the shift; and 09:00, 12:00, 15:00 and 18:00 for the day shift. Upwards on the ordinate indicates worse performance in each panel.

Results for Study B, which contained only a night shift condition, paralleled those for the night shift condition of Study A (see Fig. 4). Mixed-effects ANOVA yielded significant effects of time point for the factor scores of *steering variability* ($F_{3,618}=3.77$, $P=0.011$) and the representative metric $\mathrm{STEX}_3(S)$ ($F_{3,618}=3.71$, $P=0.012$); for the factor scores of *lane variability* ($F_{3,618}=26.3$, $P<0.001$) and the representative metric SD(L) ($F_{3,618}=28.68$, $P<0.001$); for PVT lapses ($F_{3,618}=16.2$, $P<0.001$); and for KSS sleepiness ($F_{3,618}=6.13$, $P<0.001$).

Taken together, these results for the two studies show that both *steering variability* and *lane variability* displayed moderate fatigue effects as a function of time of day in the night shift condition as compared to the day shift condition.

3.3. Correlates of simulated driving performance

Table 2 shows the correlations between the independent indices of fatigue (PVT lapses, KSS sleepiness) and the PCA factor scores for *steering variability*. For the group-average time series in Study A, there was a significant correlation between *steering variability* and PVT lapses in the night shift condition. For the collective data of the individual participants, the correlation between *steering variability* and PVT lapses in the night shift condition was smaller but also significant. As expected, there were no significant correlations for the day shift condition. For the group-average time series and the collective individual data in Study B, there were no significant correlations either. Thus, the significant correlation between *steering variability* and PVT lapses in the night shift condition in Study A was not replicated in Study B.

Table 2 also shows the results for the correlations between the independent indices of fatigue and the PCA factor scores for *lane variability*. For the group-average time series in Study A, there were significant correlations between *lane variability* and both independent indices of drowsiness in the night shift condition. For the collective individual data, the correlation between *lane variability* and PVT lapses was smaller but still significant, but the KSS no longer correlated significantly with *lane variability*. Again, as expected, there were no significant correlations for the day shift condition. For the group-average time series in Study B, as in the night shift condition in Study A, there were significant correlations between *lane variability* and both independent indices of drowsiness. For the individual data, the correlation coefficients were smaller but still significant.

Collectively, these results show that *lane variability*, more so than *steering variability*, correlated with independent markers of fatigue in the two studies.

3.4. Distinction and relation between steering variability and lane variability

The finding that steering-related and lane position-related metrics clustered on different dimensions (see Table 1) indicated that these metrics were statistically orthogonal. However, one would expect them to be related, as steering wheel movements should translate to systematic lateral position changes on straightaways. We derived the transfer function for the hardware and software of each of the driving simulators, which revealed that, in accordance with the physics of real cars, the driving simulators act as a first-order low-pass filter. That is, steering wheel movements of relatively low frequencies are passed to the wheels, whereas steering wheel movements of high frequencies are considerably dampened (see Fig. 5). This makes the relationship between steering wheel movements and lane position changes nonlinear, and explains why steering-related and lane position-related metrics did not cluster together in the PCA.

With the transfer function between steering wheel input and change in lateral lane position in hand, it should be possible to estimate the relative changes in lateral lane position based solely on the measured steering wheel angle. To examine this, we estimated changes in lateral lane position from changes in steering wheel angle using the transfer function of each of the simulators, and correlated the estimates with the actual lateral lane position signal sampled from the simulators, as illustrated in Fig. 6. Over all 10,000 straightaways in Study A, the average correlation was

Table 2
Correlations of factor scores for the *steering variability* and *lane deviation* dimensions of driving performance with two independent indices of drowsiness.

	Study A								Study B			
	Group averages				Individual data points				Group averages		Individual data points	
	Night shift		Day shift		Night shift		Day shift		Night shift		Night shift	
	r	*P*	*r*	*P*	*r*	*P*	*r*	*P*	*r*	*P*	*r*	*P*
Steering variability versus PVT lapses	0.42	0.007	0.07	0.66	0.23	<0.001	0.01	0.88	0.22	0.17	0.08	0.09
Steering variability versus KSS sleepiness	0.21	0.18	0.07	0.66	0.05	0.31	0.04	0.38	0.09	0.58	0.04	0.28
Lane deviation versus PVT lapses	0.44	0.005	0.25	0.12	0.32	<0.001	0.02	0.69	0.44	0.005	0.19	<0.001
Lane deviation versus KSS sleepiness	0.72	<0.001	0.20	0.21	0.01	0.87	0.00	0.96	0.53	<0.001	0.31	<0.001

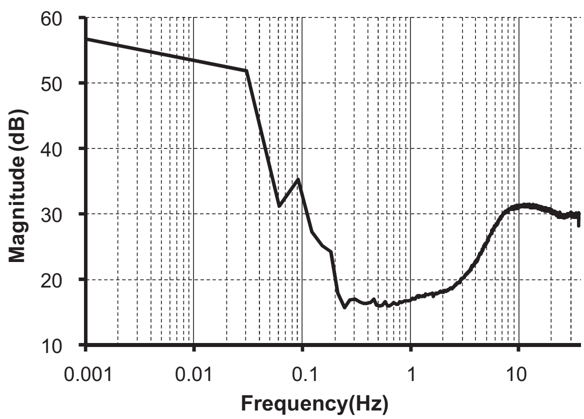

Fig. 5. Simulator transfer function between steering wheel angle and lateral lane position for simulator #1 in Study A.

$r = 0.88$ ($P < 0.001$). Over all 6,400 straightaways in Study B, it was $r = 0.78$ ($P < 0.001$). As the simulator hardware and software translating steering wheel position into changes in vehicle heading are highly realistic, we would expect to find similar correlations in real-world driving.

Computation of most lane-based metrics described in Appendix A does not require that the absolute lane position be known; relative changes in lane position that could be derived from the steering wheel angle should suffice. Indeed, the group-average and collective individual correlations between time series of the original lane-based metrics and time series of the metrics recalculated from relative changes in lane position as derived from the steering wheel angle were all high ($P < 0.001$) – see Table 3.

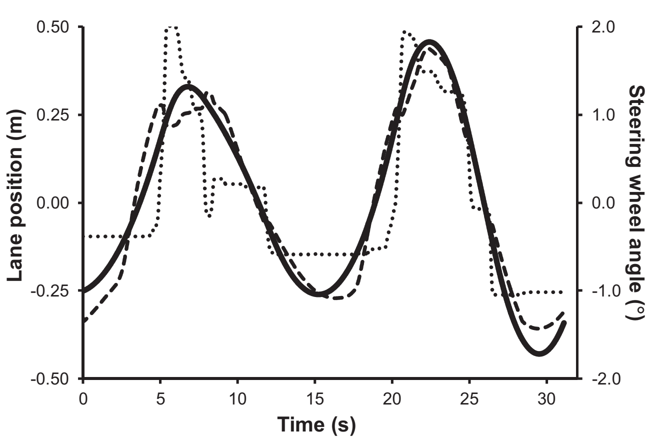

Fig. 6. Changes in lateral lane position estimated from changes in steering wheel angle. The figure shows the actual lane position (solid line), the steering wheel angle (dotted line), and the estimated lane position (dashed line) as derived from the steering wheel angle using the transfer function. This illustration is for one 0.5-mile straightaway during the 11th driving session of a participant driving on simulator #2 in the night shift condition in Study A. The correlation between the actual and estimated lane position signals for this segment was $r = 0.99$.

For the *lane variability* factor scores based on the recalculated metrics, in Study A there was a significant effect of time point ($F_{3,940} = 4.71$, $P = 0.003$) and a significant interaction of condition by time point ($F_{3,940} = 6.74$, $P < 0.001$), and in Study B there was a significant effect of time point ($F_{3,618} = 10.5$, $P < 0.001$), in agreement with what was found with the factor scores of the original *lane variability* dimension.

These results confirmed that *lane variability* could reliably be estimated from *steering variability* across straightaways in our dataset.

3.5. Curve-based results

Table 4 shows the group-average and collective individual correlations between the metrics of driving performance on straightaway segments and on curve segments in Studies A and B. All correlations between straightaway-based and curve-based metrics were significant ($P < 0.001$). Table 5 shows the average and individual correlations between the original lane-based metrics computed from curve segments and the metrics recalculated from relative changes in lane position as derived from the steering wheel angle. The correlations were all smaller than for the straightaways (cf. Table 3), but still high and significant (all $P < 0.001$). These results confirmed that *lane variability* could be estimated from *steering variability* in our dataset even across curves.

4. Discussion

This research developed a method for detecting driver drowsiness at moderate levels of fatigue. Previous work on driver drowsiness detection has been primarily concerned with high levels of fatigue when crashes tend to be imminent, which is very important but of limited use when seeking to warn a driver well in advance of experiencing significantly elevated crash risk. Reliably detecting driver drowsiness when fatigue levels are still moderate would provide the driver with sufficient time to reach a rest stop, implement a countermeasure such as caffeine intake, or otherwise prevent a drowsy driver accident. Our research provides important first steps toward developing a more comprehensive driver drowsiness detection system that is sensitive *before* fatigue levels become critical.

Using data from studies in which participants were subjected to simulated day shift and night shift schedules that included repeated driving on a high-fidelity driving simulator, we found that under conditions of negligible to moderate fatigue and at near-constant driving speed (55 mph), 87 different metrics of driving performance drawn from the literature reflected only two distinct major components of variance, namely *steering variability* and *lane variability*. As such, our research revealed that among the multitude of

Table 3
Correlations between lane position-based metrics originally calculated using the absolute lateral lane position signal sampled by the driving simulator on the one hand, and recalculated using the estimated relative changes in lateral lane position as derived from the steering wheel angle using the transfer function on the other hand, across straightaways.

Metric[a]	Study A				Study B	
	Group averages		Individual data points		Group averages	Individual data points
	Night shift	Day shift	Night shift	Day shift	Night shift	Night shift
SD(L)	0.92	0.87	0.66	0.63	0.90	0.70
DEV$_{mean}$(L)	0.90	0.88	0.61	0.61	0.87	0.67
DEV(L)	0.89	0.89	0.60	0.61	0.89	0.69
DEV$_{var}$(L)	0.83	0.82	0.44	0.42	0.87	0.67
VAR(L)	0.83	0.82	0.44	0.42	0.87	0.67

[a] Acronyms are defined in Appendix A.

Table 4
Correlations between selected metrics of driving performance on straightaway segments versus on curve segments. The factor scores for *steering variability* and *lane variability* were computed using the factor loadings obtained from the PCAs performed on metrics from straightaway segments.

Metric[a]	Study A				Study B	
	Group averages		Individual data points		Group averages	Individual data points
	Night shift	Day shift	Night shift	Day shift	Night shift	Night shift
Steering variability	0.49	0.26	0.42	0.10	0.59	0.49
Lane variability	0.35	0.17	0.44	0.26	0.11	0.27
STEX$_3$(S)	0.59	0.70	0.38	0.38	0.66	0.31
SD(L)	0.71	0.61	0.36	0.27	0.66	0.47
DEV$_{mean}$(L)	0.71	0.59	0.37	0.28	0.65	0.24
DEV(L)	0.70	0.61	0.34	0.30	0.65	0.45
DEV$_{var}$(L)	0.56	0.50	0.20	0.18	0.29	0.24
VAR(L)	0.55	0.37	0.24	0.15	0.27	0.24

[a] Acronyms are defined in Appendix A.

available metrics, there may only be a few independent components that together capture most of the variance in driving performance under conditions of fatigue. We also found that *lane variability* in particular correlated significantly with the rise in fatigue across time of day in the night shift condition (and also tracked the absence thereof in the day shift condition). This finding implies sensitivity to moderate levels of fatigue, in fulfillment of the main objective of our research.

The correlations we observed between *lane variability* and independent measures of fatigue (PVT and KSS) exceed other such correlations reported in the literature (Friedrichs and Yang, 2010; Moller et al., 2006). An exception is the work of Horne and Baulk (2004), who found a group-average correlation between KSS and lane departures of $r = 0.88$ in a 2-h simulator driving session in the afternoon following a night of sleep restriction to 5 h. Nonetheless, it has been questioned whether moderate fatigue levels reliably elicit measurable changes in driving performance in the real world (Sandberg et al., 2011b). A complicating factor in this regard is the existence of substantial, trait-like individual differences in responses to fatigue (Van Dongen et al., 2004a, 2012), the expression of which varies considerably across performance tasks (Franzen et al., 2008; Frey et al., 2004; Leproult et al., 2003; Van Dongen et al., 2004a, 2006). This is a poorly understood phenomenon, requiring a better classification of cognitive processes underlying task performance (Ratcliff and Van Dongen, 2011; Tucker et al., 2010). Our analysis of the various published driving metrics and how they cluster together contributes to this need for classification, but more detailed decompositions of driving performance are needed to really understand and predict what makes an individual vulnerable or resilient to fatigue in the context of automobile driving.

An important innovation resulting from our research is the demonstration that the transfer function between steering wheel input and change in lateral lane position can be used effectively to estimate the relative changes in lateral lane position based solely on the steering wheel angle. Lane variability is widely considered to be an important metric of drowsy or otherwise unsafe driving (Åkerstedt et al., 2010; Anund et al., 2008; Sandberg et al., 2011b), but to date has required installation of lane-tracking cameras and complex video signal processing software. Video-based lane tracking is prone to data loss when lane markers are missing or covered (e.g., by sand or snow), when weather conditions are bad, or in darkness.

Table 5
Correlations between lane position-based metrics originally calculated using the absolute lateral lane position signal sampled by the driving simulator on the one hand, and recalculated using the estimated relative changes in lateral lane position as derived from the steering wheel angle using the transfer function on the other hand, across curves.

Metric[a]	Study A				Study B	
	Group averages		Individual data points		Group averages	Individual data points
	Night shift	Day shift	Night shift	Day shift	Night shift	Night shift
SD(L)	0.65	0.68	0.67	0.69	0.62	0.63
DEV$_{mean}$(L)	0.63	0.70	0.65	0.67	0.62	0.63
DEV(L)	0.65	0.66	0.67	0.69	0.63	0.64
DEV$_{var}$(L)	0.66	0.67	0.66	0.71	0.65	0.66
VAR(L)	0.66	0.70	0.66	0.71	0.65	0.66

[a] Acronyms are defined in Appendix A.

Table A.1
Metrics of driving performance. Column one defines metric acronyms. Letters in parentheses define which signal(s) the metric was applied to. Column two describes the metrics.

Acronym (signal[a])	Description
SD(*L*, *LV*, *LA*, *A*, *V*, *S*, *AV*)	Standard deviation of signal
VAR(*L*, *LV*, *LA*, *A*, *V*, *S*, *AV*)	Variance of signal
RMS(*L*, *LV*, *LA*, *A*, *V*, *S*, *AV*)	Root-mean-square of signal
MEAN(*L*, *LV*, *LA*, *A*, *V*, *S*, *AV*)	Average of signal
SNR(*L*, *LV*, *LA*, *A*, *V*, *S*, *AV*)	Reciprocal coefficient of variation of signal variability
DEV(*L*, *S*)	Total signal deviation from windowed[b] signal average
$\mathrm{DEV}_{mean}(L, S)$	Average signal deviation from windowed[b] signal average
$\mathrm{DEV}_{var}(L, S)$	Variance of signal deviations from windowed[b] signal average
MCF(*L*, *S*, *Y*)	Most common signal frequency
E(*L*, *S*, *Y*)	Signal energy (power)
$\mathrm{TLC}_6(L, V, S, Y)$	Time to lane crossing within 6 s
$\mathrm{TLC}_{60}(L, V, S, Y)$	Time to lane crossing within 60 s
DOI([*LA*, *S*], [*Y*, *S*])	Degree of interaction between signals (see Mattsson, 2007)
SWDR(*S*)	Number of steering wheel direction reversals
$\mathrm{STEX}_{0.3}(S)$	Percentage of samples with signal amplitudes exceeding 0.3°
$\mathrm{STEX}_{3}(S)$	Percentage of samples with signal amplitudes exceeding 3°
$\mathrm{STEX}_{30}(S)$	Percentage of samples with signal amplitudes exceeding 30°
$\mathrm{STEX}_{1SD}(S)$	Percentage of samples with signal amplitudes exceeding 1 SD
$\mathrm{STEX}_{2SD}(S)$	Percentage of samples with signal amplitudes exceeding 2 SD
$\mathrm{MAXA}_{right}(S, AV)$	Maximum signal amplitude to the right
$\mathrm{MAXA}_{left}(S, AV)$	Maximum signal amplitude to the left
$\mathrm{CUMA}_{right}(S)$	Cumulative signal amplitude to the right
$\mathrm{CUMA}_{left}(S)$	Cumulative signal amplitude to the left
$\mathrm{A}_{\%right}(S)$	Percentage of samples with signal amplitudes to the right
$\mathrm{A}_{\%left}(S)$	Percentage of samples with signal amplitudes to the left
$\mathrm{MCA}_{right}(S, AV)$	Most common signal amplitude to the right[c]
$\mathrm{MCA}_{left}(S, AV)$	Most common signal amplitude to the left[c]
$\mathrm{MCA}_{\%right}(S, AV)$	Percentage of samples with signal amplitudes equaling MCA_{right}[d]
$\mathrm{MCA}_{\%left}(S, AV)$	Percentage of samples with signal amplitudes equaling MCA_{left}[d]
PHASE([*S*, *AV*])	Average radius in (*S*, *AV*) phase-plot
$\mathrm{PHASE}_{arc}([S, AV])$	Arc length of (*S*, *AV*) phase-plot
$\mathrm{PHASE}_{area}([S, AV])$	Area of (*S*, *AV*) phase-plot
ENTROPY(*S*)	Entropy of central (within ±0.005 rad) steering movements
$\mathrm{ENTROPY}_{right}(S)$	Entropy of steering movements to the right
$\mathrm{ENTROPY}_{left}(S)$	Entropy of steering movements to the left
FD(*S*, *A*, *V*)	Fractal dimension of signal
$\mathrm{RT}_{auto}(S)$	Reaction time from signal auto-correlation
$\mathrm{RT}_{cross}([S,Y])$	Reaction time from signal cross-correlation
$\mathrm{SDEV}_{mean}(V)$	Average signal deviations from 55 mph
$\mathrm{SDEV}_{SD}(V)$	Standard deviation of signal deviations from 55 mph
$\mathrm{SDEV}_{SNR}(V)$	Reciprocal coefficient of variation of signal deviations from 55 mph

[a] *L* is lateral lane position; *S* is steering wheel angle; *V* is driving speed; *A* is accelerator depression; *Y* is car yaw angle; *LV* is lateral velocity; *LA* is lateral acceleration; *AV* is angular velocity.
[b] For *L*-based metrics the window size was 20 s; for *S*-based metrics the window size was 1 s.
[c] For *S*, the number of samples in 0.005 rad bins ranging from 0 to 0.15 rad was used; for *AV*, the number of samples in 0.0005 rad/s bins ranging from 0 to 0.1 rad/s was used.
[d] For *S*, ±0.005 rad; for *AV*, ±0.0005 rad/s.

In contrast, deriving lane variability from steering wheel variability requires only a factory assessment of the car's transfer function, and a simple and easy to install sensor of steering wheel angle and an off-the-shelf signal processor. Thus, our research has yielded a cheap and consumer-friendly steering-based technology that may be further developed for driver drowsiness detection (Van Dongen and Forsman, 2011).

Our research was conducted using data from high-fidelity driving simulators with realistic hardware and software models of the forces that act on the chassis, drive train, suspension, tires, and road surface. These simulators are normally used for training of professional drivers (Hickman, 2005; Morgan et al., 2011; Pierowicz et al., 2001), and have high generalizability to the real world. Even so, we used data from standardized driving scenarios involving driving in daylight on rural highways without other vehicles or obstacles. It is critical that a field study of real-world driving be conducted to assess the validity, sensitivity and specificity of our steering-based driver drowsiness detection technology before implementation in actual cars is considered. Furthermore, the usefulness of our technology for detecting driver drowsiness at higher levels of fatigue should be investigated, as drivers may already be highly fatigued when they first get behind the wheel. Alternatively, our technology could be combined with other systems already available for detecting severe driver drowsiness, and would provide a cost-effective solution to extending the utility of such systems.

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Appendix A.

The driving simulator sampled lateral lane position (*L*), steering wheel angle (*S*), driving speed (*V*), accelerator depression (*A*), and car yaw angle (*Y*) at 72 Hz in Study A and at 60 Hz in Study B. In addition, we derived lateral velocity (*LV*) and lateral acceleration (*LA*) from *L*, and angular velocity (*AV*) from *S*. From these eight base signals we computed the 87 metrics specified in Table A.1. Of the 87 metrics, 45 were steering-related, 20 were lane-related, 15 were speed-related, two were yaw-related, and five were hybrid metrics.

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