USING MOMENTARY DERIVATIVE ESTIMATES TO GAUGE DRIVER PERFORMANCE

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ABSTRACT

Measurement of driver performance and the subsequent initiation of safety measures is of increasing interest to automotive manufactures and users. Many studies of driver performance are based on indicators that are likely to be difficult to collect in real-life conditions (e.g., lane position). These measures are easily measured in simulators, but may not be easily measured across a variety of road conditions (e.g., deterioration, roadwork, snow). To increase the possibility of implementing safety measures, the current paper examines the estimation of derivatives from in-vehicle measures of vehicle control such as steering wheel angle. At very short time scales (e.g., <1 second) many in-vehicle measures may be indicative of drivers who are making small corrections to their trajectories. Drivers making a large number of ongoing corrections may indicate characteristics such as fatigue and inattention. This paper compares derivative estimates to other common measures of driving performance and models changes in momentary derivative estimates in a 90-minute simulation with 19 participants.

Keywords: new methods, derivative(s), measurement, attention, performance, lateral velocity, time series analysis

INTRODUCTION

While in the past the focus of automobile safety has been placed on factors such as car and road design (e.g., impact testing and debate about appropriate speed limits) recent years have seen a shift in focus. Increasingly issues of automobile safety are related to how involved the driver is with the task of driving the car. More focus is being placed on topics such as the effects of cell phones, text messaging, and drowsy drivers --- in short, the attention resources being placed on the task. The last example, drowsiness, is perhaps the most interesting because it reveals the beginning of a new paradigm; in recent years several car manufactures have begun to incorporate systems intended to alter driver behavior when they are showing indications of drowsiness. This is likely to be the beginning of many such systems.

The keys to any driver performance safety system are the measures and indicators used to assess driver performance. Many studies of driving behavior use indicators that are likely to be difficult to collect in real-life conditions. Indicators such as variance in lane position are likely to be difficult to achieve in real life as snow or poorly maintained roads are likely to lead to poor measurements (e.g., Volvo, 2007). To increase the possibility of implementing safety measures, it is necessary to consider measurements that are easily obtainable from inside the vehicle; measurements such as steering wheel angle and accelerator movement.

The current paper examines the possibility of using derivative estimates of in-vehicle measures to provide moment-to-moment indicators of driving performance. The current paper limits itself to thinking about highway-like driving conditions; in particular driving conditions where the driver is expected to maintain consistent inputs for relatively long periods of time, compared to the stop-and-go patterns observed in city driving. This focus is selected, as the data presented were collect with the intention of examining attentional declines related to long-distance driving and distractors such as phone calls.

Derivatives

Without information regarding variables exogenous to a vehicle, it may seem that only limited performance information can be gained. Measures such as steering angle don't seem to provide the same absolute measure of performance provided by measures such as lane position. One set of measures that may be informative, however, is how the driver is making changes to in-vehicle measures. Is the driver making slow, gradual changes? Abrupt changes? Lots of minor corrections?

Changes in a variable with respect to another variable are often expressed as derivatives. Several derivatives can be calculated, each which can provide different information regarding the status of a car. Using steering angle as an example, the zeroth derivative is the angle of the steering wheel at a given point in time. Thinking about highway driving, and a snapshot of the steering wheel angle at any given time, it is apparent that this measure is unlikely to highlight poor driving behavior unless the driver has turned the wheel to an unusually large angle --- in which case a warning system is unlikely to be helpful, as large steering angles and highway speeds don't tend to coincide for very long.

The first derivative is the amount of change observed in the steering wheel angle over a given period of time. Unlike the zeroth derivative, the first derivative gives information about changes in steering angle. This information could be interpreted various ways, including whether the driver is making frequent or infrequent course corrections. The second derivative, which is the change in the first derivative with respect to time, indicates the rate at which the driver is making changes to the steering wheel angle. Acceleration in steering angle may be a key indicator to erratic or aggressive driving behavior, as actions such as swerving will produce large acceleration values (high rate of change in speed of steering angle). In considering driver input, taking into account the derivatives of measured variables may be useful in gaining insight to driver performance, as each derivative may correspond to different driving behavior.

Time Scales

Even when derivatives are taken into account, a key piece of information that is overlooked is the time scale over which the derivatives are calculated. Thinking about the change in steering angle reported by a simulator at any moment, the values are likely to represent a variety of sources --- steering wheel angle changes due to a turn in the road, momentary fluctuations of the driver, and even changes estimated due to error in electronics of the car/simulator. The observed steering angle at any time, and consequently the instantaneous derivatives, are the sum of these various sources. Focus on derivatives over differing time scales may provide different pieces of information regarding the actions of the driver.

The idea of multiple sources of input, and interest in only a select range of the variability --- for example interest in the driver fluctuations but not in variability due to the road curving or electronic error --- is well known in the time series and signal processing literatures (e.g., Gasquet & Witomski, 1999; Gottman, 1981). It is not unusual in signal processing to use a high pass filter to remove the lowest frequencies; in this case these frequencies representing gradual changes in the average of the steering angle could represent the car going through long turns on a highway. Similarly, low pass filters can be used to eliminate the highest frequencies; in this case the very highest frequencies are likely to be error generated by the electronics used. When such error is not present in a data set, it is likely that the car/simulator creators have already used some sort of low pass filter. In all cases these filters are used to eliminate frequencies or components that may be undesirable.

The same can be done using derivative estimates. The calculation of a derivative estimate consists of gauging the change in one variable with respect to another variable. For this paper, focused will be placed on change of the in-vehicle measures with respect to time. Derivatives of a time series could be estimated over many different time scales. At the shortest time scales (e.g., <500ms) the derivatives will reflect only momentary fluctuations more reflective of actions to keep one centered in one's lane and is unlikely to reflect actions such as a long curve on a highway. At moderate time scales (e.g., a few seconds) we might be able to capture fluctuations in the derivatives that are more indicative of moderate movements such as shifting lanes. At very long time scales (e.g., >30 seconds) the derivatives might be more indicative of a turn in the highway.

Derivative estimates are similar to linear filters, such as the decomposition of time series into sine waves (Fourier Analysis). Both derivative estimates and Fourier Analysis can be used to remove components from data that are unlikely to represent the variability of interest. However, we make use of derivative estimates because derivative estimates lend themselves to interpretations that are more difficult to achieve with sine waves. While one can discuss changes in power of parts of the Fourier Spectrum, talking about position, speed and acceleration of the steering wheel or car seems almost natural as these terms are frequently used in reference to cars. This language advantage would also seem to extend when we wish to discuss things like the variability in steering angle speed --- is the person making a lot of consistent changes or a mixture of small and large steering angle changes? --- something that is less intuitively expressed in the frequency domain (Deboeck, Montpetit, Bergeman, Boker, 2009).

Goals

This paper will examine the first derivative of two quantities: steering angle and lateral position; That is, we will examine changes in steering velocity and changes in lateral velocity. This latter measure can be calculated from car based measures by taking into account the rate at which the steering wheel is being turned and the forward speed of the car. These measures will be compared to absolute measures of driving performance, such as the variance in lane and the variance in the difference between the road angle and car angle. Both a short (100ms) and moderate (10s) time scale are examined. Individual models are then built to examine the effects of several predictors on the estimated derivatives.

METHOD

Participants & Data

Data was collected using a STISIM model M100. Nineteen college students from a midwestern university each drove in the simulator for 110 miles (approximately 90 minutes[1]). Participants drove for approximately 80 minutes, before being interrupted by a phone call. This condition was intended to generate variations in the attention of the driver, including decreased attention due to the length of the task and potential stimulation/distraction due to the phone call late in the trial. The simulation included a variety of common driving events, including: coming to a full stop (braking events), billboards, speed limit signs, curving roads, and both oncoming and same-direction traffic. Events, items and cars became visible at 1500ft, about 13.5 seconds at 75 mph. Details of the simulation are shown in Figure 1.

[1] Drivers were expected to drive at between 70 and 77 mph. An alarm was used when the driver exceeded 77 mph.

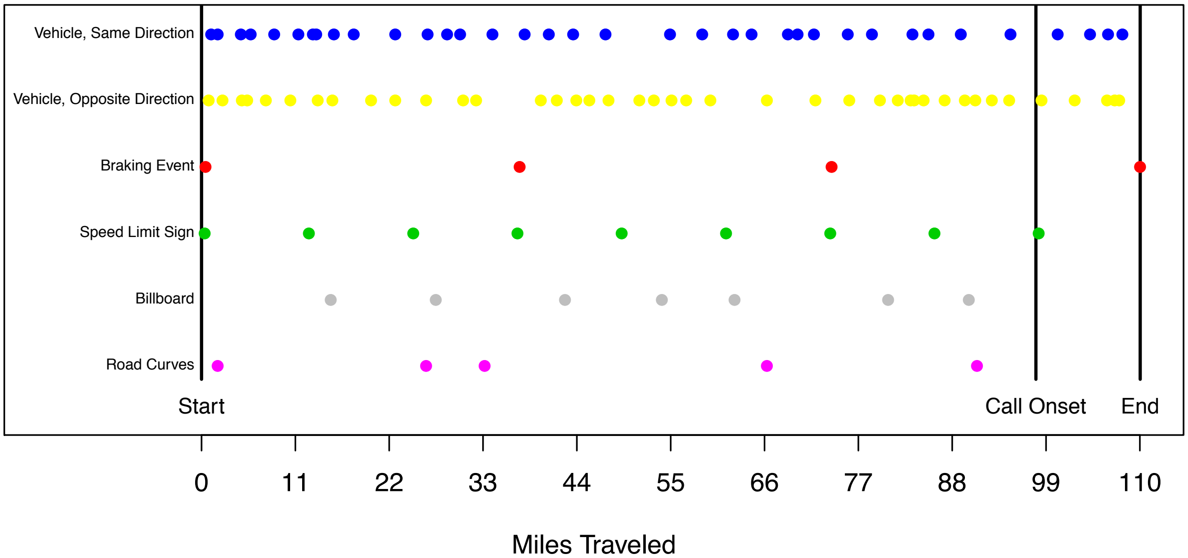

Figure 1: Detail of the occurrence of events during the simulation; Circles represent an occurrence of an event listed on the left hand side. The start of the simulation, end of the simulation, and the call onset are represented with vertical lines.

Analyses

Two sets of analyses were conducted. The first set of analyses examined two measures based on derivative estimates: first derivatives of steering angle and first derivatives of lateral position; that is, the steering velocity and lateral velocity. Driving time series were divided into windows of a specific length (e.g., 100ms). Within each window the steering and lateral velocity were calculated using Generalized Local Orthogonal Derivative Estimates (GOLD, Deboeck, 2010). GOLD estimates use a set of orthogonal polynomials in order to produce estimates of differing orders of derivatives. Absolute values of the derivative estimates were used as the interest was in how quickly the subject was turning the wheel or how quickly the car was moving laterally, not whether the movement was positive or negative (i.e., right or left).

Within each window the variance in lane position and variance in the difference between road angle and car angle was calculated. These absolute measures of performance were compared to the derivative based measures. In some cases the observed values being used were transformed using a square-root transformation,[2] this was done for two reasons: 1) to spread out distributions that were highly positively skewed, and 2) to show nearly linear equivalence between some pairs of measures. As the relationships between the derivative and variance measures were expected to depend on the time scale examined, analyses were repeated for both a short (100ms) and moderate (10s) time scale.

[2] The square-root transformation was used because of its ability to handle values of zero, which naturally occur more frequently for both derivative and variance estimates as the window of observation is reduced. Values of zero are problematic for other commonly used transformations of skewed distributions such as the log transformation and the inverse transformation.

The second set of analyses examined the effects of the experimental conditions on the momentary derivative outcomes. This analysis focused on 100ms estimates of lateral velocity; the purpose of this analysis was to replicate results that would be expected with other measures of performance such as variance in lane position. The square-root of the absolute lateral velocity estimates were used as the dependent variable. Performance was predicted using time (rescaled to reflect the effect of a 10-minute interval), an intercept change due to the onset of the phone call (call intercept), a change in the effect of time due to the call (call slope), and two intercept differences that might occur due to the interruption of the drive midway by two full-stop braking events (brake 1 and brake 2). Two variables coded 0, 1 were also used to indicate the presence of billboards (signs) and curves in the road (curves); A value of 1 was used from 1500ft before the occurrence of a sign or curve (when they became visible) until one mile after the event occurred.

With 100ms windows the typical trial for a subject produced about 54,000 observations on the dependent variable, which resulted in significant computational problems. Time series were therefore down-sampled such that only every 20th window was analyzed --- that is, only the first 100ms of every consecutive 2s window was analyzed (about 2,700 observations per subject). Models were fit to each individual separately, in order to make no assumptions about the similarity of effects across individuals; statistics calculated on the group may be a poor reflection of the results for any given individual (Boker, Leibenluft, Deboeck, Virk & Postolache, 2008; Molenaar, 2004). After initially using linear regression, the partial autocorrelation was calculated on the residuals; This analysis suggested a lack of independence between observations, with a moderate lag-1 correlation and higher lag correlations that tended to be of small magnitude and inconsistent across individuals. A generalized least squares (GLS) model was therefore used to allow for a lag-1 correlation between errors; The AIC for the GLS model was smaller for every individual than the linear regression model.

RESULTS

Figure 2 shows several plots comparing the absolute steering velocity and absolute lateral velocity measures to the measures of variability in lane position (standard deviation) and variability in the difference between road angle and car angle (standard deviation). The two columns of the figure reflect that there are substantial differences that occur depending on the time scale examined, and that the apparent relationship between the derivative and variability measures dramatically drops off when one averages over a relatively small period of time (10s). It should be noted that while less correlated, the information in Figure 2D does suggest that when the standard deviation of lane position gets large --- for example, 5ft which should only occur with lane changes --- this could be predicted using the moderate scale 10 second estimates of lateral velocity. Studies interested in behavior such as frequent lane changes, which might indicate erratic driving, may need to examine time scales other than those examined here.

Over the 100ms windows, there is a strong relationship between the absolute measures of performance and the car-based derivative measures of performance. In particular, Figure 2C suggests that momentary estimates of lateral velocity are directly related to momentary estimates of variability in lane position. It is this relationship that consequently led to the used of 100ms estimates of lateral velocity as the dependent measure in the second set of analyses.

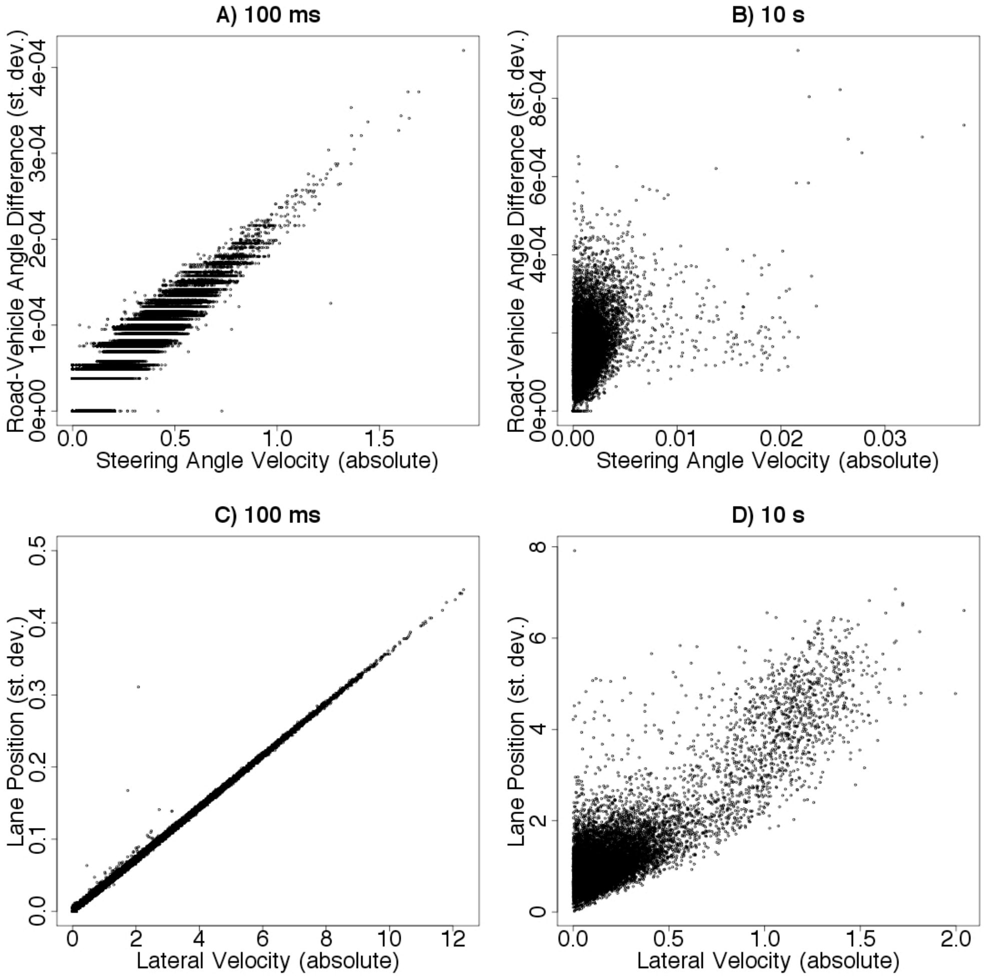

Figure 2: Plots of Steering Angle Velocity (top row) and Lateral Velocity (bottom row) compared to common measures of driver performance (variability in Road-Car Angle Difference and Lane Position) using time scales of 100ms and 10s (left and right columns)

In the second set of analyses the momentary changes in lateral velocity were predicted using time, call intercept, call slope, brake 1, brake 2, signs, and curves; Models were fit separately on each individual, allowing for a unique lag-1 autocorrelation between the residuals for each participant. Table 1 compiles the results across the 19 participants. The mean and standard deviation of the 19 estimates for each parameter are reported, as well and the minimum, median, and maximum parameter estimates observed; For each distribution of parameters a *p*-value is reported, corresponding to the test whether the average of the distribution of parameters differs from zero.

The results in Table 1 suggest that on average the momentary estimates of lateral velocity are increasing with time (β=0.032, p<0.0005), suggesting that on average drivers are making an increasing number of momentary changes to the direction of the vehicle over the course of the 90-minute trial; Note this is the effect for a 10-minute period of time. On average the call that interrupts the drive in the 80th minute leads to a large decrease in the number of small corrections being made by drivers (β=-0.153, p<0.0005). The slope of the dependent variable during the phone call (last 10 minutes) does not appear to significantly differ from the change in performance due to time (β=-0.003, p=0.65). The full-stop breaking events appear to lead to a subsequent decrease in making corrections, seemingly negating some of the effect of fatigue (β=-0.065, p<0.0005 and β=-0.069, p<0.0005). Neither billboard signs nor curves in the road appear to have an effect on the momentary lateral velocity (β=0.003, p=0.66 and β=0.004, p=0.76 respectively).

Table 1: Analysis of parameter estimates produced by GLS regression model.

Parameter	Mean of Estimate	Standard Deviation	p-value	Minimum	Median	Maximum
(Intercept)	0.825	0.119	<0.0005	0.609	0.838	1.113
Time (10 min)	0.032	0.024	<0.0005	-0.008	0.033	0.084
Call (Intercept)	-0.153	0.102	<0.0005	-0.341	-0.151	0.050
Call (Slope, 10 min)	-0.003	0.025	0.65	-0.049	-0.003	0.068
Brake 1	-0.065	0.059	<0.0005	-0.186	-0.065	0.051
Brake 2	-0.069	0.062	<0.0005	-0.204	-0.070	0.028
Signs	0.003	0.030	0.66	-0.036	-0.008	0.067
Curves	0.004	0.052	0.76	-0.122	-0.001	0.080

The results in Table 1 are only representative of what is occurring for participants on average. If predictors have differential effects, for example if some people are distracted by billboards while they stimulate others, on average there may be no effect. Table 2 shows the significance of different predictors within individual; this subsample was selected to highlight differences observed between subjects. As 7 predictors are being examined on 19 subjects (133 statistical tests), conventional cutoffs are not recommended and a stricter α-level should be used when examining this table[3]. There are substantial differences apparent in how people are affected by the predictors. Within this small subsample, there are people who do and don't show effects of time, effects of the call onset (intercept), effects of continuing to talk on the phone (call slope), effects of the braking events, and there is even one person who appears to be affected by curves in the road! The one predictor on which people are similar is that of billboards (signs, no effect).

Table 2: Test of parameter significance, within participant, for the four participants shown in Figure 5.

Parameter	Participant #3	Participant #10	Participant #14	Participant #19
Time (10 min)	p=0.0015	p=0.0003	p<0.0001	p=0.81
Call (Intercept)	p=0.0008	p=0.34	p=0.0001	p=0.0001
Call (Slope, 10 min)	p=0.99	p=0.0005	p=0.63	p=0.24
Brake 1	p=0.41	p=0.07	p=0.002	p=0.30
Brake 2	p=0.14	p=0.0002	p=0.0001	p=0.53
Signs	p=0.80	p=0.31	p=0.32	p=0.91
Curves	p=0.79	p=0.0005	p=0.08	p=0.98

Figure 3 plots loess-smoothed representations of the momentary lateral derivative estimates with the model-fitted values overlaid in red. From examining these figures and the significant effects in Table 2, we can visualize some of the differences between participants. Participant 3 shows

[3] An overly-conservative Bonferroni correction would indicate that using a cutoff of α=0.00038 should result in more more than a 5% chance of making one or more Type I errors across all 133 tests. A less conservative cutoff of α=0.002 will result in a 20% chance of making one Type I error and a 3% chance of making more than 1 Type I error accross all 133 tests, assuming the tests are independent of each other.

fatigue over time, but few effects due to braking, signs and curves --- although the call onset does produce a change in behavior. Participant 10 also shows fatigue, reactions to braking and curves in the road, but relatively little reaction to the onset of the call in the 80th minute --- although this participant does seem to show less momentary changes to lateral velocity the longer he talks on the phone. Participant 14 is similar to participant 3, although curves and signs may affect this participant a little more. And participant 19 is very much unlike the others --- showing almost no effects of time, braking, signs and curves --- although there is again a large decrease in momentary changes following the call onset.

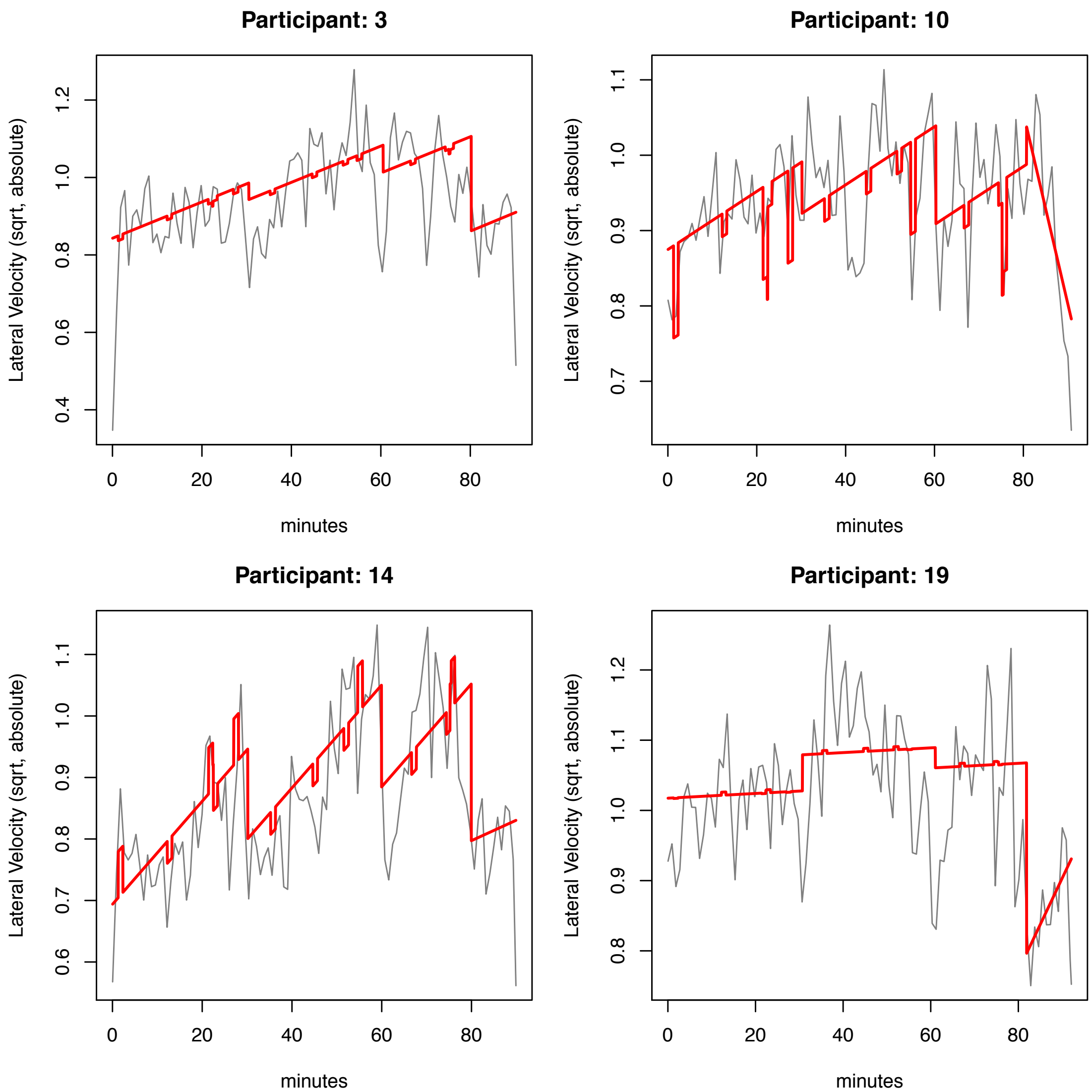

Figure 3: Sample of results from 4 participants. Gray lines are loess smoothed values (1-minute window) of the square-root of the absolute lateral velocity (100 ms). The red lines are the GLS fitted values allowing for autocorrelated errors with a lag of one.

CONCLUSIONS

Focus in driving performance studies is often placed on measures that are not easily obtained from within vehicles, and often average performance scores over large periods of time and across people. In this paper we have examined how very short-term derivative estimates of lateral velocity – based on in-car measurements of steering angle and speed – can be used to produce results that are similar to other commonly used measures. Figure 2 showed a close correspondence between short-interval variability in lane position and momentary changes in lateral velocity. The analysis for Table 1 showed that across individuals these momentary derivative measures produced results that would be expected based on estimates of variance in lane position averaged over long periods of time --- effects of fatigue, the effect of an interruption during a long drive, but no effects of billboards and curves across individuals. Table 2 and Figure 3 highlight that the average results in Table 1 don't necessarily apply to any one individual --- there are substantial individual differences, even in the relatively simple conditions of a simulation.

These results suggest that momentary derivative estimates may be a valuable way of gauging driver performance using only in-vehicle measurements. While these estimates are not necessary for studies of driving behavior in simulators, where measurements such as variability in lane position are easily made, these estimates may provide a way to gauge driver performance that can be more readily implemented in real-world driving scenarios where precise measurements of many variables are likely to be impossible across a variety of road conditions (e.g., lane markers). These results also suggest the need for studies to move beyond factors that affect subjects on average. It is necessary that vehicle safety systems take into account that the same event (e.g., music, phone calls) may have different effects depending on when they occur and depending on the individual experiencing the event. Systems that generalize over individuals and conditions could lead to dangerous consequences.

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