LATERAL CONTROL IN A DRIVING SIMULATOR: CORRELATIONS WITH NEUROPSYCHOLOGICAL TESTS AND ON-ROAD SAFETY ERRORS

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Summary: Driving simulators provide precise information on vehicular position at high capture rates. To analyze such data, we have previously proposed a time series model that reduces lateral position data into several parameters for measuring lateral control, and have shown that these parameters can detect differences between neurologically impaired and healthy drivers (Dawson et al, 2010a). In this paper, we focus on the "re-centering" parameter of this model, and test whether the parameter estimates are associated with off-road neuropsychological tests and/or with on-road safety errors. We assessed such correlations in 127 neurologically healthy drivers, ages 40 to 89. We found that our re-centering parameter had significant correlations with five neuropsychological tests: Judgment of Line Orientation ($r = 0.38$), Block Design ($r = 0.27$), Contrast Sensitivity ($r = 0.31$), Near Visual Acuity ($r = -0.26$), and Grooved Pegboard ($r = -0.25$). We also found that our re-centering parameter was associated with on-road safety errors at stop signs ($r = -0.34$) and on-road safety errors during turns ($r = -0.22$). These results suggest that our re-centering parameter may be a useful tool for measuring and monitoring ability to maintain vehicular lateral control. As GPS-based technology continues to improve in precision and reliability to measure vehicular positioning, our time-series model may potentially be applied as an automated index of driver performance in real world settings that is sensitive to cognitive decline. This work was supported by NIH/NIA awards AG17177, AG15071, and NS044930, and by a scholarship from Nissan Motor Company.

INTRODUCTION

Maintaining lateral control within the correct driving lane is a key aspect of safe driving. Driving simulators can give precise information regarding lateral vehicular positioning in a virtual world, often at high capture rates (e.g., 10-100 Hz). From a modeling perspective, it is unclear how to reduce the data into a meaningful measure of lateral control. Previous models have considered a reference trajectory based on position and orientation feedback to control the travel of a robotic device (Egerstet, 2001) or allowed a vehicle to track lane center via dynamic models of motion (Peng, 1990). Although these models work well, they are directed towards controlling vehicles without driver input. On the other hand, Dawson et al. (2010a) proposed a specific time series model which applies the idea of trajectory and feedback to driver induced lateral position. This model found that four of the six model parameters were significantly different between drivers with mild Alzheimer's disease (AD) and drivers without neurological impairment. One parameter ("γ_1") measured how quickly a driver tends to re-center the vehicle as it approaches the lane boundary. In that report, neurologically-healthy drivers had re-centering values that averaged 40% higher (better) than drivers with AD. The goal of the current research was to assess whether (1) neuropsychological measures of cognition, vision, and motor skills are associated with the simulator-base re-centering parameter in unimpaired drivers and (2) the simulator-based re-centering parameter is associated with on-road safety errors that were measured in an instrumented vehicle (Figure 1).

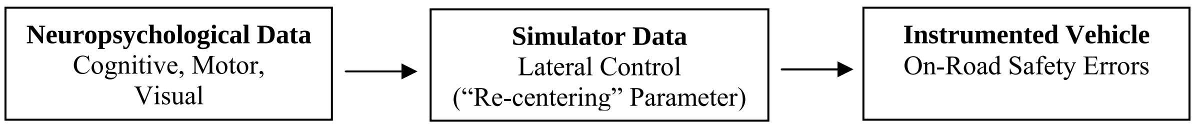

Figure 1. Three types of variables considered

METHODS

Subjects

Data were collected for 127 middle-aged and elderly drivers (age 40–89) from Iowa City and surrounding areas. All participants were required to have a valid state driver's license and were currently driving at the time of the study. In addition, these subjects had no history of neurological diagnoses or cognitive decline based on self-report of the patient on standard medical questionnaires and family corroboration. The University of Iowa institutional review board approved this study and informed consent was collected in accord with university and federal guidelines.

Neuropsychological Data

Cognitive, visual and motor task data were collected for all participants in this study. The cognition tests included in the off-road neuropsychological battery were the Complex Figure Test (CFT)–Copy & Recall, Block Design Subtest of the Wechsler Adult Intelligence Scale–Third Edition (Blocks), Benton Visual Retention Test (BVRT), Trail Making Test (TMT): Parts A & B, Rey Auditory Verbal Learning Test (AVLT), Judgment of Line Orientation (JLO), Controlled Word Association (COWA), as well as a composite measure of CFT-Copy, CFT-Recall, Block Design, BVRT, TMT-B, AVLT, JLO, and COWA. In addition to these, vision tests were administered, including Useful Field of View (UFOV), contrast sensitivity (CS), logmar scores of near/far visual acuity (NVA/FVA), and Structure from Motion (SFM). Motor ability was measured via Functional Reach, Get-Up and Go, and Grooved Pegboard.

Simulation Data

Data Collection. Simulation data was collected using the Simulator for Interdisciplinary Research in Ergonomics and Neuroscience (SIREN) (Rizzo, 2004). The simulator is a fixed base four-door 1994 GM Saturn SL2, in which electronic sensors and miniature infrared video cameras record driver performance. There are three screens to the front; one to the rear along with four LCD projectors with image generators which allow the research team to create a virtual driving environment. High frequency data (30 Hz), including steering, acceleration, and braking control are collected. Specifically, lane position from an approximately 2 minute long segment of straight road was accumulated for this study.

Data Reduction via the Time Series Model. We now review the model previously presented by Dawson et al (2010a). For an individual drive, let the time, t, be on the horizontal axis of the coordinate plane and Y_t represent the lane position (in meters) of the center of the vehicle at time, t, be on the vertical axis (see Figure 2). We scaled the lateral control measure such that $Y_t = 0$ when the center of the vehicle is in the center of the lane. In addition, when $Y_t > 0$, the vehicle is to the left of the center of the driving lane (from the driver's perspective) and when $Y_t < 0$, the vehicle is to the right of the center of the driving lane (tending towards the right shoulder).

The general form of a third order autoregressive time series model (Kendall & Ord. 1990) with a signed error term for $t > 3$ is given by

$$Y_t = g(Y_{t-1}, Y_{t-2}, Y_{t-3}) + |e_t|\, I_t, \qquad (1)$$

where $e_t \sim N(0, \sigma^2)$ and $p_t = \mathrm{Prob}(I_t = -1)$, else $I_t = 1$.

In the general form, g(.) is an unknown function predicting lateral position at time t based on the three previous observed lateral positions; e_t is a normally distributed error (residual) term between the observed and predicted lateral position at time t; σ^2 is the variance of this residual term; and I_t is a sign indicator, equaling 1 and – 1 with probability p_t and $1 – p_t$ respectively. In a more specific form, the g(.) function contains three parameters related to flat, linear, and quadratic projections based on previous time points. Regarding p_t, it is logical to have p_t increase as Y_t shifts from 0 to positive values, as increasing values of Y_t indicate that the vehicle is drifting towards the left shoulder and would require a high probability of a negative error ($I_t = -1$) to re-center the vehicle to the right. Similarly, when Y_t is decreasing, the vehicle is moving toward the right shoulder, and a positive error ($I_t = 1$) would be needed to move the vehicle back to the center of the driving lane. This situation would require p_t to be low, so that the probability of a positive error would be high.

Although many functional forms could be applied to model the relationship of p_t with lateral position, logistic regression was chosen to match the work presented by Dawson et al. (2010a):

$$\log\left(\frac{p_t}{1-p_t}\right) = \gamma_0 + \gamma_1 Y_{t-1} \qquad (2)$$

where γ_0 is the intercept term of the logistic model, γ_1 is the slope of the logistic model, and Y_{t-1} is the lane position at the last time point. We note that γ_0 represents a subject's natural center, which may or may not be the center of the lane. If $\gamma_0 > 0$, for example, the subject's average lane position would be right of the lane center, while $\gamma_0 < 0$ would represent an average position that is left of center.

The focus of this paper is the "re-centering parameter," γ_1. Higher values of γ_1 represent an increased likelihood for a driver to re-center the vehicle as a lane boundary is neared, and generally reflect safer driving. Figure 2 illustrates data from two different values of γ_1. Although the natural driving center of the vehicles differ, we can note from the oscillatory pattern in each diagram that the driver with a low γ_1 value (on the right) tends to make longer drifts towards the shoulder, with relatively few lateral corrections, whereas the driver with a high value (on the left), remains closer to the center of the driving lane, with more lateral corrections.

After collecting data on each subject for a 120-second drive on a straight stretch of road, the data were filtered by taking averages of every five frames, resulting in 6 Hz data (e.g., 167 msec intervals). These averages were then used to fit our time series model in SAS, as detailed by Dawson (2010a). The re-centering parameter estimates were used in correlational analyses with neuropsychological test scores (describe above) and with safety errors in an instrumented vehicle (described in next section), using Spearman correlations.

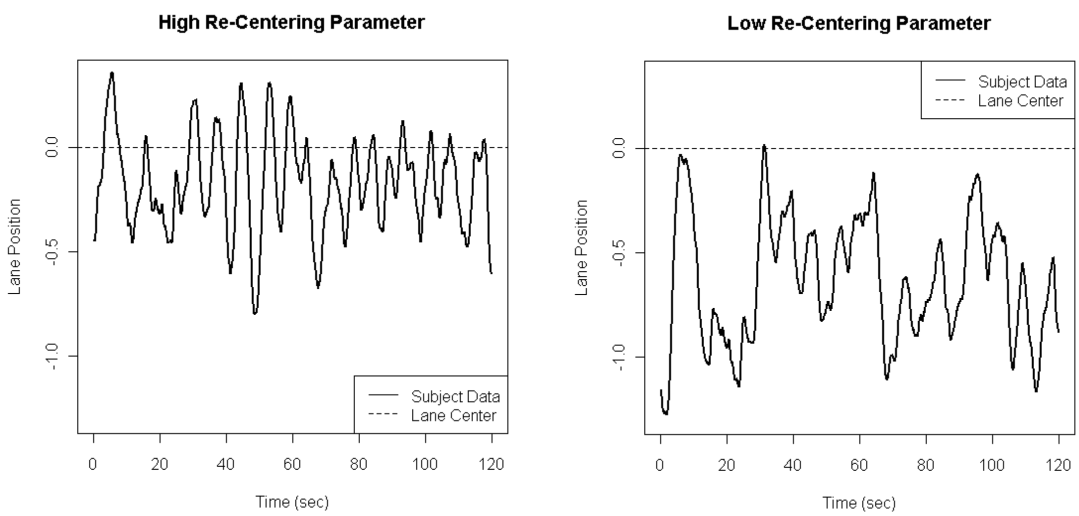

Figure 2. Plots of lateral positioning data with high and low re-centering parameter values

Instrumented Vehicle

The Automobile for Research in Ergonomics and Safety (ARGOS) is an instrumented vehicle (IV) with an automatic transmission, concealed sensors, and unobtrusive lipstick-sized cameras for observations of naturalistic driving (Rizzo et al, 1997). Electronic driving data such as steering position, normalized accelerator, and velocity were recorded at 10Hz. In addition, the drive was recorded in order to obtain video of driver behavior as well as exterior video of forward field of view and the front tires.

After an acclimating drive, subjects drove an 18-mile route of two-lane and four-lane roads in a mix of urban and rural settings. The road test was conducted only under good weather conditions and during daylight hours. In addition, training and quality control protocols were adhered to in order to avoid inconsistencies in both route and instructions given to the driver.

After the drive was completed, the videos were reviewed by a professional driving instructor; not present during the drive (Dawson et al, 2009; Uc et al, 2009; Dawson et al, 2010b). The frequency, type and location of driving safety errors were recorded, with errors observed in 13 different categories: starting and pulling away from the curb, traffic signals, stop signs, turns, lane observance, lane changes & merging, speed control, parallel parking, railroad crossings, curves, overtaking, backing up, and miscellaneous. The five most common—lane observance, turns, stop signs, speed control, and lane changes & merging—were considered for this study.

RESULTS

Several neuropsychological and on-road driving errors were related to the re-centering parameter at the 5% alpha level. The significant correlations are shown in Table 1, where the arrows indicate the direction of better performance on the test listed (e.g., higher scores are better for Judgment of Line Orientation). All of the correlations are in the expected direction, with better scores on these variables being associated with higher re-centering parameters.

Table 1. Spearman correlations of neuropsychological tests & on-road errors with re-centering parameter in 127 neurologically-normal drivers

Type	Variable	Test Mean (SD)	Correlation	p-value
Neuropsychological	Judgment of Line Orientation ↑	25.13 (4.02)	0.378	<0.0001
Neuropsychological	Block Design Test ↑	38.06 (9.96)	0.269	0.0026
Neuropsychological	Contrast Sensitivity ↑	1.82 (0.15)	0.313	0.0004
Neuropsychological	Near Visual Acuity ↓	0.02 (0.05)	-0.260	0.0033
Neuropsychological	Grooved Pegboard ↓	89.18 (18.60)	-0.246	0.0057
Instrumented Vehicle	Stop Sign Errors ↓	3.72 (1.94)	-0.342	0.0003
Instrumented Vehicle	Turn Errors ↓	5.49 (2.85)	-0.217	0.0227

DISCUSSION

When dealing with electronic data captured at high frequencies in driving simulators, it is desirable to reduce data into a few parameters to assess driver performance. Our time-series model, which is scaled in the time domain, provides an interpretable re-centering parameter. In this study, we found that this had significant correlations with five neuropsychological tests in unimpaired drivers: Judgment of Line Orientation, Block Design, Contrast Sensitivity, Near Visual Acuity, and Grooved Pegboard. This suggests that this parameter is clinically relevant, as slight decline in cognitive ability may be able to predict worse performance in re-centering a vehicle. We also found that our re-centering parameter was associated with on-road safety errors at stop signs and with on-road safety errors during turns, suggesting that this simulator-based measure may have real-world validity. In sum, our findings suggest that the re-centering parameter may be a tool to help long-term monitoring of elderly or impaired drivers, and it also has potential as an index of acute changes, such as fatigue or medication side effects.

This study has a number of limitations. First, although they are significant, our correlations were somewhat modest, implying that our re-centering parameter might not have high enough sensitivity and specificity in predicting on-road errors at the individual level. Second, we performed 22 hypothesis tests based on correlations, which increases the chance of making Type I errors. So, among our seven statistically significant findings, there may be one or two that are spurious. Additionally, although our re-centering parameter estimates appear to give satisfactory results in our data, the statistical properties of our estimating procedure have not yet been studied via computer simulations. Such simulation studies could likewise make comparisons of our approach with other time domain approaches as well as with frequency domain approaches. Moreover, our method of analysis made no attempt to separate out the anticipatory perception level versus the compensatory level of driving behavior, as was presented by Donges, 1978.

Although our model was developed for lateral positioning data, it may also be applied to steering wheel position data and to lateral acceleration. These types of data are readily available in driving simulators and in instrumented vehicles, so we can compare the results of our model across these two platforms. Lateral positioning data are also available in instrumented vehicles via GPS technology; however, the capture rate, precision, and reliability of such technology does not yet appear to be adequate for applying our methods to data from GPS. As this technology improves, our model has the potential to be part of warning devices that give immediate or long-term feedback regarding driving performance.

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