MEASURING THE SAFETY IMPACT OF ROAD INFRASTRUCTURE SYSTEMS ON DRIVER BEHAVIOR: VEHICLE INSTRUMENTATION AND EXPLORATORY ANALYSIS

Justin Schorr
justin11@gwmail.gwu.edu*
Traffic and Networks Research Laboratory
The George Washington University
Exploration Hall
20101 Academic Way
Ashburn, Virginia 20147

Samer H. Hamdar
hamdar@gwu.edu
Traffic and Networks Research Laboratory
The George Washington University
Exploration Hall
20101 Academic Way
Ashburn, Virginia 20147
Phone: (202) 994 6652
Fax: (202) 994 0127

Claire Silverstein
Traffic and Networks Research Laboratory
The George Washington University
Exploration Hall
20101 Academic Way
Ashburn, Virginia 20147

ABSTRACT

Featured in this pilot experimental study is the construction and design of an instrumented vehicle that is able to capture vehicle trajectory data with an extremely high level of accuracy and time resolution. Once constructed and properly instrumented, the various data collection systems were integrated with one another and a driving experiment was conducted on Northern Virginia roadways with 18 participants taking part in the study. Trajectory data was collected for each of the drivers as they traversed a predefined loop of four roadway segments with varying number of lanes as well as shoulder widths. Data collected from the experiment was then used to calibrate the parameters of the prospect theory car-following model utilizing a genetic algorithm calibration procedure. Once all model parameters were successfully calibrated, significance testing was carried out to determine the impacts that the varying roadway infrastructure had on driving behavior. Results indicated that there were significant changes in behavior when comparing one lane roadways to their two lane counterparts – specifically in cases where the roadway featured a wide shoulder. Additional testing was conducted to ensure that there was no variation based on gender as 9 study participants were female and 9 were male. The successfulness of this first study conducted using the newly constructed instrumented vehicle creates the opportunity for a variety of additional studies to be conducted in the future.

INTRODUCTION

Roadway infrastructure impacts driving behavior which, in turn, has significant implications when analyzing vehicle to vehicle interactions and assessing macroscopic transportation network performance. The main question of interest is: how does the road surrounding environment affect the aggressive (risk attitudes) driving behavior from a traffic flow theory perspective? In order to address this question, the objective of this research in to conduct a real-world driving experiment featuring a vehicle instrumented to collect trajectory, location and vehicle diagnostic data. Data from this experiment is then utilized to explicitly formulate the structure of the relationship between various car-following model parameters and one of the geometric features (shoulder width/median type) shown to be significant in previous studies (Hamdar and Schorr, 2013).

Motivation and Contribution

Various methods of vehicle instrumentation have been utilized over the past 40 years in an effort to gain additional insights into the factors that contribute to decreased safety on roadways (Lenne, 2013). If total collisions are considered a surrogate measure for safety, the motivation for the examination of the different factors leading to unsafe driving conditions is highlighted by the 5,615,000 collisions that occurred on United States roadways in 2012 (an increase from the three previous years) (NHTSA, 2012). Additionally, these collisions resulted in 33,561 fatalities (an increase from the previous two years), and when considering vehicles miles travelled (VMT) as a measure of congestion the problem is exacerbated as the total VMT in 2012 was 2,969 billion, producing a fatality rate of 1.13 fatalities per 100 million vehicle miles travelled (both the total VMT and the fatality rate have increased over the past two years) (NHTSA, 2012). What becomes clear is that in the past couple of years roadways are trending in a direction that is both less safe and increasingly congested.

Objectives

As stated above, the main objective of this study is to understand the impact that changes in roadway geometry have on driving behavior from a traffic flow theory perspective. In order to develop this understanding, the specific objectives of this study are as follows:

- Construct an instrumented vehicle such that trajectory and headway data can be collected at a high time resolution and subsequently synced together
- Design a real-world driving experiment utilizing the instrumented vehicle on roadway segments with varying geometric characteristics
- Calibrate the parameters of the prospect theory model using the data gathered from the driving experiment
- Determine the effects that specific roadway geometric characteristics have on driving behavior through statistical analysis of calibrated model parameters

BACKGROUND

While data driven approaches (predominately focused around the modelling and evaluation of collision data) are commonplace in the transportation research community, new and affordable technologies have led to advancements in the collection of real-time driving data. The quantification of driving behavior in real-time is an important advancement in the assessment of roadway safety – allowing for new insights through a variety of different methodologies and their subsequent applications. Three main approaches are used for the collection of real-time data: driver simulators, naturalistic studies and instrumented vehicles; all of which have an associated set of pros and cons.

Driver simulators have been used extensively in a wide range of applications including (but not limited to) assessment of driver distraction (Young et. al, 2014), the performance of active safety and information systems (Liu and Wen, 2005), and the evaluation of impaired drivers (Akerstedt et al., 2005) as well as those with certain medical conditions (Frittelli et al., 2009). Driver simulators are particularly useful as they allow for simulated driving experiences to be conducted in a safe and controlled environment where various scenarios (including complicated and high-risk environments) can be created and held constant for all participants in a given study (Bifulco et al., 2012). However, the obvious drawback to these studies is that they do not take place on actual roadways, and are unable to capture the natural interactions that occur between drivers in the real-world environment (Carston et al., 2013). As such, on-road data collection methods such as naturalistic studies and instrumented vehicles are becoming increasingly popular in order to better understand road safety crash risks and risk factors (Lenne, 2013).

Naturalistic approaches utilize unobtrusive methods (typically in participants' own vehicles) to collect data in real traffic conditions (Lenne, 2013). Again, the applications naturalistic studies are vast, including (but not limited to) examination of risks to heavy vehicle operators through the use of data acquisition systems, internal and external cameras, and daily activity registers (Soccolich et al., 2013); assessment of heavy vehicle operator response to a forward collision warning system through the use of gaze monitoring and brake pedal position (Wege et al., 2013); examination of older driver engagement in secondary activities at intersections through the use of a video camera system as well as a vehicle diagnostic logging system (Charlton et al., 2013); and the analysis of rapid deceleration events for older drivers through the use of a custom driver monitor system which featured a two-axis accelerometer (Keay et al., 2013). Naturalistic studies allow for the collection of large amounts of data (both in terms of the number of participants and the number of trips made) over an extended period of time. Furthermore, the instruments used to collect data are unobtrusive (Chamadiya, 2010) and these types of studies do not require a researcher to be present in the vehicle during data collection. (The collection of this "baseline" data is intended to reflect "normal driving" (Carsten et al., 2013). However, practical and analytical challenges are commonplace in naturalistic studies as datasets are large and complicated, often requiring the processing of hundreds or even thousands of hours of vehicle-based and video data (Lenne, 2013). Additionally, since no variables are controlled by the researcher, causal conclusions cannot be drawn from naturalistic driving studies (Carsten et al., 2013).

Similar to naturalistic studies, field operational tests (FOT) are long range studies and again involve some sort of instrumentation. In these studies objective data on situation and behavior is collected through an automated process and subjective data is usually collected manually or electronically (Carsten et al., 2013). In addition to these naturalistic studies, field operational tests and driver simulator experiments, controlled on-road studies involving instrumented vehicles offer opportunities for unique data collection through the use of multiple methods (Lenne, 2013). These controlled on-road studies are defined by their reliance on a pre-defined route in order to determine differences in performance and behavior under varying driving conditions (Carsten et al., 2013). Furthermore, from a behavior perspective, field studies utilizing instrumented vehicles are frequently regarded as the ultimate validation stage for assessing behavioral models, safety measures and improved road infrastructure design (Santos et al., 2005). Still, the potential drawbacks of these controlled on-road studies must be mentioned as the studies do not collect data over a long time period (Lenne, 2013) and they require a researcher to be present in the vehicle (potentially impacting the driver's behavior) (Lenne, 2013; Carsten et al., 2013). With that being said, these types of studies are well suited to address research questions that are independent of exposure and that utilize independent factors that are stable over shorter periods of time (such as age and personality); and are excellent tools in the early stages of system development and FOT design (one example of this being a situation where drivers' headway is affected; and thus the need for additional sensors (such as lidar sensors) is required) (Carsten et al., 2013). Examples of studies utilizing this type of instrumented vehicle data collection include examination of the number and nature of errors committed by drivers in distracted and undistracted states (Young et al., 2013), analysis of the situational awareness of both novice and experienced drivers at rail crossings (Salmon et al., 2013), and evaluation of an intersection violation warning prototype (Brewer et al., 2011). In addition, instrumented vehicles have been used in driver training through the benchmarking of experienced drivers (Underwood, 2013).

In addition to the behavioral applications mentioned above, driver simulators, field studies and instrumented vehicles can allow for collection of trajectory data in order to assess and calibrate car-following models. Car-following models describe the behavior of the following vehicle as a function of the lead vehicle's trajectory, allowing for estimation or prediction of the following vehicles' trajectory in response to the actions of the lead vehicle (Soria et al., 2014). Driver simulator experiments have been conducted to evaluate car-following behavior under both normal and evacuation scenarios (Xu et al., 2012) and field tests have been conducted using loop detector data to determine distance gaps under different congestion regimes (Dijker et al., 1998). While these types of studies are most certainly useful in understanding car-following behavior, instrumented vehicles allow for more detailed data collection and thus have been used frequently in both data collection and calibration efforts (Soria et al., 2014).

Examples of instrumented vehicles being used for data collection and the assessment of driver behavior variability in car-following include two studies by Brackstone et al. (2002; 2009) where headways for drivers following the instrumented vehicle were recorded in the first study, and then the research was extended (in the second study) to study the factors that influence the decision making process of car following. While the drivers in Brackstone's studies knew they were part of an experiment, Kim et al. (2007) used an instrumented vehicle equipped with an infrared sensor, a differential GPS (DGPS) inertial distance measuring instrument, a vehicle computer and a digital video camera to measure the position, speed and acceleration (as well as demographic information collected from the video recordings) of the following vehicles who were unaware that they were being monitored as part of the study. In an effort to quantify driver reaction times, Ma and Andreasson (2006) equipped a vehicle developed by Volvo Technologies with a GPS system, an on-board computer, two lidar sensors (facing front and rear), as well as cameras corresponding to the sensors. The study was conducted on Stockholm roadways and the "follow-the-leader" behaviors of random vehicles behind the instrumented vehicle were observed.

Once data from instrumented vehicles is collected, the next step in evaluating car-following models is the calibration stage. One such study was conducted by Panwai and Dia (2005) who evaluated AIMSUN, PARAMICS and VISSIM models using instrumented vehicle data collected in Stuttgart, Germany. In this case, the instrumented vehicle was equipped with radars to record the differences in speed and headway between the instrumented vehicle and the vehicle immediately in front of it (Manstetten et al., 1997). Similarly, Punzo and Simonelli (2005) examined Newell's model, the Gipps model, an intelligent driver model and the MITSIM model though the use of trajectory data recorded from four instrumented vehicles. Here, the four vehicles were all instrumented with GPS devices and Global Navigation Satellite System receivers (GLONASS) to record vehicle spacing data and drove in a platoon on both urban and "Sextraurban" roadways in Naples, Italy (Punzo et al., 2005). One final example of a study focused around car-following model calibration using data from instrumented vehicles was conducted by Soria et al. (2014). Here, a Honda Pilot SUV was equipped with four wide coverage digital cameras, a Honeywell Mobil Digital Recorder, a GPS system and a laptop to record geographical position, speed, spacing, left-right turn signal activation, video clips and audio recordings. The instrumented vehicle was positioned as the follower and only the front camera was used to determine the spacing between the leader and the follower (Soria et al., 2014). The authors then used the data obtained from the instrumented vehicle to calibrate the Gipps model, the Pitt model, the MITSIM model and the Modified Pitt model.

RESEARCH METHODOLOGY

Vehicle Instrumentation

The Instrumented Vehicle used for data collection in this experiment is comprised of three systems working in unison; a lidar system, a DGPS system and an OBD (on-board diagnostics) monitoring system. Data from all three systems is received by an in-vehicle laptop – which generates a local timestamp for synchronization purposes. A schematic for the vehicle instrumentation (overlaid on a laser scan of the actual vehicle) is provided in Figure 1; Table 1 then lists the various components.

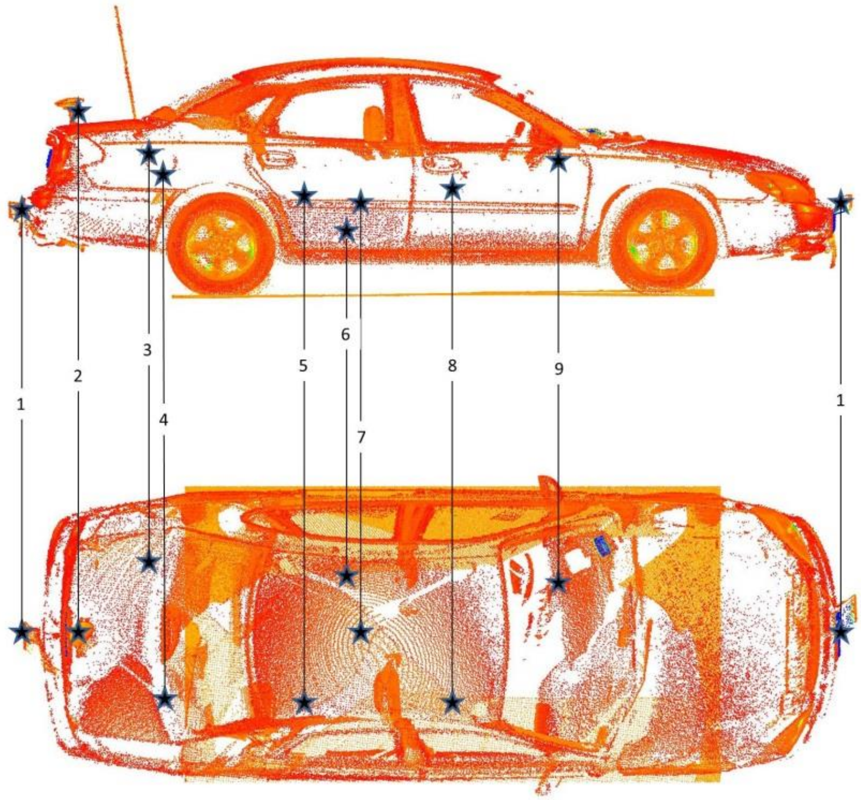

FIGURE 1 Vehicle Instrumentation.

TABLE 1 Vehicle Instrumentation Key

Instruments		
Number	***Instrument Name***	***Data Collected***
1	Lidar Sensors (2)	Trajectory Data
2	DGPS Antenna	Vehicle Position Data
3	External Computing Unit	
4	Sync Box	
5	Ethernet Switch	
6	DGPS Receiver	Vehicle Position Data
7	Power Box	
8	Laptop	
9	On-board Diagnostics Logger	Vehicle Diagnostic Data

Experimental Set-up

The driving experiment in this study allows for observation of moment-by-moment local interactions among drivers, and measures drivers' preferred traffic measures with known attributes (gender, age, and attitude). Furthermore, experimental set-up involves testing one of the exogenous geometric factors shown to impact safety. For this pilot study, the authors have selected shoulder width/number of lanes as the test variables and a driving experiment was conducted in an interrupted flow scenario. Figure 2 displays a GoogleEarth© image of the Northern Virginia roadway segments selected for this experiment generated by the differential GPS data recorded during experimentation. The black line in the figure is the actual DGPS path travelled by a study participant, and the base stations zdc11910 and lwx11910 (used to increase the accuracy of the DGPS recordings) are seen in the top left and bottom center of the figure. Additionally, each of the four segments is highlighted in the figure where the red lines mark the start and/or end point of a segment. Segment one is a two lane roadway with a wide shoulder, Segment two is a one lane roadway with a wide shoulder, Segment three is a two lane roadway with a narrow shoulder and Segment four is a one lane roadway with a narrow shoulder. For the experiment, 18 drivers (9 male and 9 female between the ages of 20 and 33) drove the instrumented vehicle through all four roadway segments. Drivers were instructed to behave as they would normally, with the exception that they were not permitted to pass the lead vehicle at any point during the test run. The lead vehicle was operated by an author of this study and speed was varied (+/- 7 mph from the posted speed limit) on as consistent of a basis as possible (given the surrounding traffic conditions), at the same locations throughout each of the four segments.

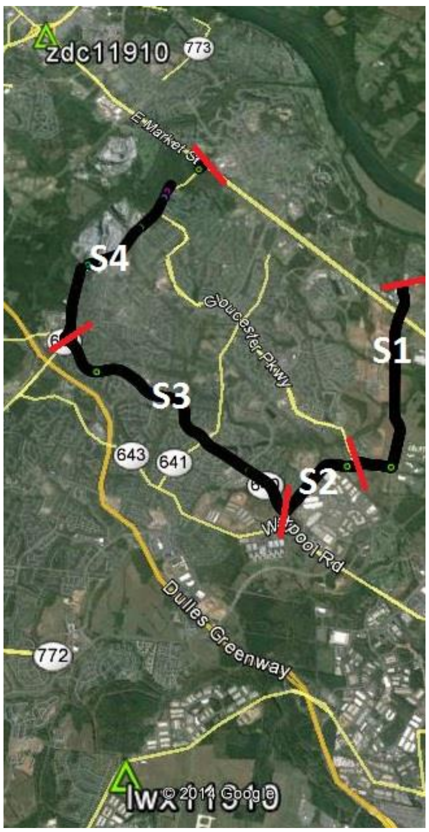

FIGURE 2: Roadway segments used in this pilot study

Modelling and Calibration

Drivers evaluate their acceleration choice options based on the resulting potential gains and losses. Prospect theory (Kahneman and Tversky, 1979) has been used to model this decision making process (Hamdar et al., 2008). Here, drivers frame the stimulus where different utilities are assigned to different acceleration choices considering different weights for gains and losses;

and then "edit" the choices based on a prospect index calculated in the same way as expected utility are calculated. The prospect theory value function is formulated as:

$$U_{PT}(a_n) = \frac{\left[w_m + (1 - w_m)(\tanh\left(\frac{a_n}{a_0}\right) + 1)\right]}{2}\left[\frac{\left(\frac{a_n}{a_0}\right)}{1 + \left(\frac{a_n}{a_0}\right)^2}\right]^{\gamma} \quad (1)$$

Where U_{PT} is the acceleration value function, a_0 is the normalization parameter, $\gamma > 0$ is a sensitivity exponent indicating how sensitive a driver is towards gains or losses in travel times (i.e. speeds), and w_m is the relative weight of losses compared to the gains. Here, a driver choosing a_n as his/her desired acceleration will gain U_{PT} unless he/she is involved in a rear-end collision. Furthermore, a crash seriousness term $k(v, \Delta v)$ is used to calculate the disutility resulting from a crash as follows:

$$U(a_n) = (1 - p_{n,i})U_{PT}(a_n) - \mathrm{p_{n,i}} w_c \mathrm{k}(v, \Delta v) \quad (2)$$

Where $p_{n,i}$ is the subjective probability of being involving in a crash at the end of a car-following duration; $p_{n,i}$ is approximated by a normal distribution given that drivers are assumed to estimate the future speed $v_{n-1}(t + \Delta t)$ of vehicle *n-1* to be normally distributed with a mean equal to the current speed $v_{n-1}(t)$ and a standard deviation of $\alpha * v_{n-1}(t)$ (α is a velocity uncertainty parameter); $U_{PT}(a_n)$ is derived from equation 1 and w_c is a crash weighting function which is lower for drivers willing to take a higher risk.

Trajectory data recorded by the instrumented vehicle (velocity, acceleration and space headway) at a resolution of 0.1 seconds is used to calibrate the model presented above. Since headway data was not always recorded at the same time resolution as the vehicle motion data, values were interpolated based on the change in vehicle velocity between recorded headway values. Calibration was then performed on a segment by segment basis for each driver using a genetic algorithm procedure. Following the genetic algorithm description of Hamdar (2009):

1. A "chromosome" represents a parameter set of the prospect theory model discussed above and a population consists of N_{GA} such chromosomes.
2. In each chromosome generation, the fitness of each chromosome is determined via an objective function.
3. All pairs of chromosomes are extensively generated from the current population and recombined to generate new chromosomes.
4. The cross-over point where two chromosomes are combined is randomly selected
5. Excluding the chromosome with the best fitness score, all genes (model parameters) are mutated (random variation) based on a given probability. The newly generated chromosomes are then used in the next iteration.
6. Initially, a fixed number of generations are evaluated. The evolution is then terminated when the best-of-generation score converges from one iteration to another for a given number of generations.

RESULTS AND DISCUSSION

Calibration Results and Significance Testing

Table 2 displays the descriptive statistics for the calibration results. This includes the average and standard deviation values for the calibration parameter, velocity and space and time headways for each segment. Additionally, these descriptive statistics are provided for geometric characteristics (number of lanes and shoulder width) and gender in Tables 3, 4 and 5 respectively.

TABLE 2 Descriptive Statistics for All Segments

Segment	Stat	Vel (m/s)	Space (m)	Head (s)	ψ	γ	Wm	Wc	Tmax	α	β	Tcorr	RT (s)	Vel Error
1	Avg	15.18	33.03	2.21	5.97	0.73	3.66	89833	5.26	0.21	6.33	17.83	0.63	0.173
	Dev	1.60	7.94	0.66	3.73	0.62	2.18	23796	1.57	0.09	3.39	5.23	0.73	0.074
2	Avg	13.99	33.09	2.41	5.40	1.09	2.83	97944	4.83	0.11	7.08	20.39	0.36	0.100
	Dev	1.07	13.12	1.14	4.90	0.72	1.98	16913	2.07	0.06	2.81	4.02	0.36	0.056
3	Avg	14.71	30.52	2.10	5.64	0.63	4.11	95000	5.16	0.19	5.60	20.83	0.72	0.169
	Dev	1.14	6.99	0.55	4.50	0.46	2.24	25752	0.91	0.06	2.90	4.59	0.53	0.072
4	Avg	15.70	29.69	1.90	4.27	0.71	3.94	100778	5.67	0.13	6.63	20.22	0.62	0.137
	Dev	1.50	7.46	0.48	3.91	0.58	2.46	19283	1.72	0.06	3.03	3.81	0.47	0.059

TABLE 3 Descriptive Statistics for Number of Lanes

Lanes	Stat	Vel (m/s)	Space (m)	Head (s)	ψ	γ	Wm	Wc	Tmax	α	β	Tcorr	RT (s)	Vel Error
1	Avg	14.84	31.39	2.16	4.83	0.90	3.39	99361	5.25	0.12	6.86	20.31	0.49	0.119
2	Avg	14.95	31.77	2.15	5.81	0.68	3.88	92417	5.21	0.20	5.96	19.33	0.68	0.171

TABLE 4 Descriptive Statistics for Shoulder Widths

Shoulder	Stat	Vel (m/s)	Space (m)	Head (s)	ψ	γ	Wm	Wc	Tmax	α	β	Tcorr	RT (s)	Vel Error
Wide	Avg	14.58	33.06	2.31	5.68	0.91	3.25	93889	5.05	0.16	6.71	19.11	0.49	0.137
Narrow	Avg	15.21	30.10	2.00	4.96	0.67	4.02	97889	5.42	0.16	6.11	20.53	0.67	0.153

TABLE 5 Descriptive Statistics for Males and Females

Gender	Stat	Vel (m/s)	Space (m)	Head (s)	ψ	γ	Wm	Wc	Tmax	α	β	Tcorr	RT (s)	Vel Error
Female	Avg	15.01	27.00	1.82	5.48	0.62	3.49	94861	5.25	0.14	6.68	20.06	0.653	0.143
Male	Avg	14.78	36.16	2.49	5.16	0.96	3.78	96917	5.21	0.18	6.14	19.58	0.514	0.147

In order to interpret the statistical significance of the change in calibration parameters based on number of lanes, shoulder width and gender, multiple MANOVA tests were conducted (using the SAS software). Results of the MANOVA test indicate whether or not you can reject the null hypothesis – the null hypothesis being that a certain exogenous characteristic has no statistically significant effect on the change in calibration parameters. For statistical significance and the rejection of the null hypothesis, the p-value must be less than 0.05. Tables 6 displays the MANOVA results for the effects of number of lanes, shoulder width and gender on the calibration parameters. In addition, the effect of changing segments is included at the top of this table to demonstrate that the null hypothesis can be rejected for the change in segments. If the null hypothesis could not be rejected for the changing segments as a whole, then there would be no statistical significance of the calibration results for this study.

TABLE 6 General MANOVA Testing

Segment			
Statistic	**Value**	**F Value**	**P Value**
Wilks' Lambda	0.484	1.84	0.0106
Pillai's Trace	0.615	1.78	0.0146
Hotelling-Lawley Trace	0.872	1.90	0.0094
Roy's Greatest Root	0.571	3.93	0.0005
Shoulder Width			
Statistic	**Value**	**F Value**	**P Value**
Wilks' Lambda	0.784	1.90	0.0684
Pillai's Trace	0.216	1.90	0.0684
Hotelling-Lawley Trace	0.276	1.90	0.0684
Roy's Greatest Root	0.276	1.90	0.0684
Lanes			
Statistic	**Value**	**F Value**	**P Value**
Wilks' Lambda	0.688	3.13	0.0036
Pillai's Trace	0.312	3.13	0.0036
Hotelling-Lawley Trace	0.454	3.13	0.0036
Roy's Greatest Root	0.454	3.13	0.0036
Gender			
Statistic	**Value**	**F Value**	**P Value**
Wilks' Lambda	0.787	1.86	0.0745
Pillai's Trace	0.213	1.86	0.0745
Hotelling-Lawley Trace	0.271	1.86	0.0745
Roy's Greatest Root	0.271	1.86	0.0745

From the table, it is clear that a change in the number of lanes has the most statistically significant effect on the change in the calibration parameters. With this in mind, the data set was separated based on shoulder width and a MANOVA test was again conducted for the number of lanes. These results are displayed in Table 7.

TABLE 7 MANOVA Testing for Changing Number of Lanes Based on Shoulder Width

No shoulder – Changing Lanes			
Statistic	**Value**	**F Value**	**P Value**
Wilks' Lambda	0.717	1.14	0.3704
Pillai's Trace	0.283	1.14	0.3704
Hotelling-Lawley Trace	0.395	1.14	0.3704
Roy's Greatest Root	0.395	1.14	0.3704
Wide shoulder – Changing Lanes			
Statistic	**Value**	**F Value**	**P Value**
Wilks' Lambda	0.555	2.31	0.0458
Pillai's Trace	0.445	2.31	0.0458
Hotelling-Lawley Trace	0.801	2.31	0.0458
Roy's Greatest Root	0.801	2.31	0.0458

Here, it is clear that the null hypothesis cannot be rejected when considering a change in the number of lanes on roadways with narrow shoulders, but it can be rejected for a change in the number of lanes on roadways with wide shoulders.

Finally, to ensure that there was no statistically significant difference based on gender, a final MANOVA test was carried out for each segment using gender as the dependent variable. These results (Table 8) demonstrate that the null hypothesis cannot be rejected based on gender for any of the segments.

TABLE 8 MANOVA Testing Based on Gender by Segment

Segment 1 - Gender			
Statistic	**Value**	**F Value**	**P Value**
Wilks' Lambda	0.364	1.56	0.2725
Pillai's Trace	0.636	1.56	0.2725
Hotelling-Lawley Trace	1.749	1.56	0.2725
Roy's Greatest Root	1.749	1.56	0.2725
Segment 2 - Gender			
Statistic	**Value**	**F Value**	**P Value**
Wilks' Lambda	0.235	2.90	0.0745
Pillai's Trace	0.765	2.90	0.0745
Hotelling-Lawley Trace	3.258	2.90	0.0745
Roy's Greatest Root	3.258	2.90	0.0745
Segment 3 - Gender			
Statistic	**Value**	**F Value**	**P Value**
Wilks' Lambda	0.372	1.50	0.2895
Pillai's Trace	0.628	1.50	0.2895
Hotelling-Lawley Trace	1.687	1.50	0.2895
Roy's Greatest Root	1.687	1.50	0.2895
Segment 4 - Gender			
Statistic	**Value**	**F Value**	**P Value**
Wilks' Lambda	0.466	1.02	0.4940
Pillai's Trace	0.534	1.02	0.4940
Hotelling-Lawley Trace	1.148	1.02	0.4940
Roy's Greatest Root	1.148	1.02	0.4940

Discussion of Results and Parameter Explanation

Based on the significance testing conducted above, results from this pilot experimental study indicate that drivers change their behavior significantly on roadways with wide shoulders when there are a varying number of lanes. With this in mind it is important to interpret the parameter values from segments one and two (displayed above in Table 2). Interpretation of the changes in the calibration parameters between these two segments requires an explanation of the "physical meaning" for each of the parameters individually. Beginning with the gamma parameter (γ), this can be thought of as a driver's sensitivity to perceived gains and losses. That is if the value function of the Prospect Theory model generally has the form seen in Figure 3, increasing gamma would be indicative of an increase in the amplitude of the curve derived from Equation 1.

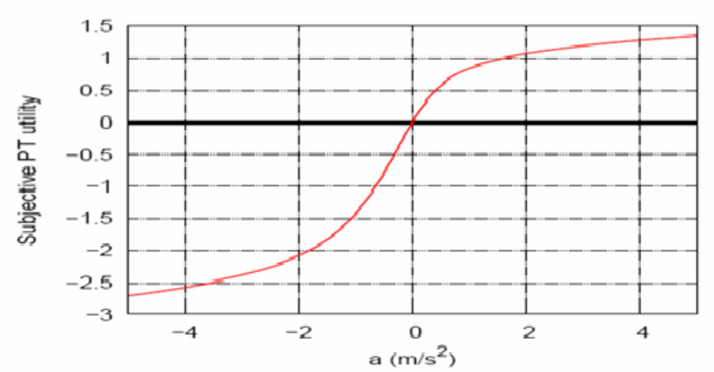

FIGURE 3 Prospect Theory Value Function (Hamdar, 2009)

Furthermore, the parameter w_m represents the relative weight a driver puts on losses as compared to gains. Increases in this parameter are therefore indicative of a driver who is "valuing" potential risks more than that of potential gains, i.e. becoming more risk adverse. Increasing the alpha parameter is indicative of a driver being more uncertain of the leader vehicle's velocity, and the beta parameter can be thought of as the drivers' sensitivity to the surrounding environment. Increasing the beta parameter could be indicative of a number of things including a more experienced driver or one that has become impatient. The Tmax parameter can be thought of as the anticipation of the driver as increasing values indicate a driver that is thinking multiple steps ahead and decreasing values indicate a driver who has a myopic view and is thinking about what is occurring "in the moment".

Looking at the changes in average calibrated values for these parameters between segments one and two we see that the one lane segment (segment two) features higher values for beta and gamma and lower values for alpha, Tmax and w_m. The combined effects of increased gamma and decreased w_m demonstrate that not only is the driver putting less weight on perceived losses, but they are also increasing their sensitivity to their perceived gains and losses. This result is further explained by an increase in the beta parameter which, in combination with the effects discussed above, seems to indicate that drivers became increasingly impatient during this segment of the experiment. Reaffirming this notion is the decrease in the value for Tmax which demonstrates that drivers are thinking more in the moment, rather than anticipating what maneuvers they may make in the future (which seems to indicate a growing level of frustration). Finally, the largest percentage decrease in any parameter value is seen in that of alpha – indicating that the driver is very certain of what the vehicle in front of them is doing, once again reaffirming the notion that drivers became increasingly impatient and frustrated while traversing this segment of the experiment.

In addition to the driving environment discussed above, significance testing indicated that drivers change their behavior when moving between one and two lane roadways in general. The most significant changes in terms of the individual calibration parameters are seen in that of alpha, beta and gamma. Here we once again observe that drivers on one lane roadways are much more certain of the lead vehicle's velocity (decreased alpha), become increasingly sensitive to their environment (or potentially increasingly impatient – increased beta), as well becoming increasingly sensitive to perceived gains and losses (increased gamma – with a slight decrease in the risk aversion parameter w_m).

While the changes in calibration parameters were not statistically significant for shoulder width or gender, it is interesting to observe that drivers had a higher average velocity, lower space headway and thus much lower time headway on roadways with narrow shoulders. That is, when shoulder width narrowed drivers followed much more closely to the lead vehicle. The same was true when comparing female drivers to male drivers, as female drivers had an average time headway that was nearly 0.7 seconds less than their male counterparts. These changes in average values were not observed when comparing one lane to two lane roadways, as the average velocity, spacing and time headway was almost identical in this case.

CONCLUSIONS AND FUTURE WORK

This pilot experimental study featured the construction of an instrumented vehicle that was able to successfully capture high time resolution trajectory data through the use of multiple instruments working in unison. Furthermore, a driving experiment was successfully conducted with 18 participants driving a predefined “loop” that featured four segments with varying number of lanes and shoulder widths. Data collected from the driving experiment was then effectively calibrated using a genetic algorithm calibration procedure. Finally, significance testing was conducted on the calibrated parameters for the prospect theory value function and results indicated that there were significant changes in driver behavior for varying number of lanes – specifically when the roadway featured a wide shoulder as opposed to a narrow one.

Research conducted in this study differentiated itself from that of previous studies not only with the combination of instruments that were used, but also in the accuracy and time resolution of the data that was collected. Further differentiating this study from previous works, the driving experiment that was conducted tested the differences in behavior based on changing roadway geometry and then used the collected trajectory data to successfully calibrate the parameters of the prospect theory car following model.

Given that this was the “pilot” experimental study for the instrumented vehicle, construction and data synchronization posed significant challenges that needed to be overcome before the actual driving experiment could take place. With these major obstacles out of the way, opportunity abounds for additional driving experiments to be conducted with a seemingly limitless potential for different types of experimental set-ups. Furthermore, the vehicle used in this study was constructed in such a manner that additional instruments can easily be integrated in the vehicle and instrumentation design; once again opening the door for a wide variety of future applications and testing.

ACKNOLEDGEMENT

The authors would like to extend their deepest gratitude to the participants that kindly took the time to take part in this study. This material is based upon work supported by the National Science Foundation under Grant No. 0927138. Any opinions, findings, and conclusions or recommendations in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

REFERENCES

Akerstedt, T., Peters, B., Anund, A., Kecklund, G., 2005. Impaired alertness and performance driving home from the night shift: a driving simulator study. *Journal of Sleep Research, 14,* 17–20.

Bifulco, G., Pariota, l., Galante, F., and Fiorentino, A., 2012. Coupling Instrumented Vehicles and Driving Simulators: opportunities from the DRIVE IN Project. *15th International IEEE Conference on Intelligent Transportation Systems.* Anchorage, Alaska, USA, September 12-19, 2012.

Brackstone, M., Sultan, B., McDonald, M., 2002. Motorway driver behaviour: studies on car following. *Transportation Research Part F: Traffic Psychology and Behaviour, 5,* 31-46.

Brackstone, M., Waterson, B., McDonald, M., 2009. Determinants of following headway in congested traffic. *Transportation Research Part F: Traffic Psychology and Behaviour, 12,* 131-142.

Brewer, J., Koopmann, J., Najm, W., 2011. System Avoidance Assessment of Cooperative Intersection Collision Avoidance System for Violations (CICAS-V). *Transportation Research Record.*

Carsten, O., Kircher, K., & Jamson, S., 2013. Vehicle-based studies of driving in the real world: The hard truth?. *Accident Analysis and Prevention*, *58*, 162-174.

Chamadiya, B. , Gharbi, A., Kunze, C. ,Wagner, M., 2010. Unobtrusive in-vehicle biosignal instrumentation for advanced driver assistance and active safety. *IEEE Biomedical Engineering and Sciences,* 252-256.

Charlton, J., Catchlove, M., Scully, M., Koppel, S., & Newstead, S., 2013. Older driver distraction: A naturalistic study of behavior at intersections. *Accident Analysis and Prevention*, *58*, 271-278.

Dijker, T., Bovy, P., Vermijs, R., 1998. Car-Following under Congested Conditions: Empirical Findings. *Transportation Research Record*, *1644*, 20-28.

Frittelli, C., Borghetti, D., Iudice, G., Bonanni, E., Maestri, M., Tognoni, G., Pasquali, L., Ludice, A., 2009. Effects of Alzheimer's disease and mild cognitive impairment on driving ability: a controlled clinical study by simulated driving test. *International Journal of Geriatric Psychiatry*, *24*, 232–238.

Hamdar, S., & Schorr, J., 2013. Interrupted versus uninterrupted flow: a safety propensity index for driving behavior. *Accident Analysis and Prevention*, *55*, 22-33.

Hamdar, S., Mahmassani, H., 2009. Life in the Fast Lane. *Transportation Research Record*, *2124*, 89-102.

Hamdar, S., Treiber, M., Mahmassani, H., Kesting, A., 2008. Modeling Driver Behavior as Sequential Risk-Taking Task. *Transportation Research Record*, *2088*, 208-217.

Kahneman, D., Tversky, A., 1979. Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Economic Society,47,* 263-292.

Keay, L., Munoz, B., Duncan, D., Hahn, D., Baldwin, K., Turano, K., 2013.Older drivers and rapid deceleration events: Salisbury Eye Evaluation Driving Study. *Accident Analysis and Prevention*, *58*, 279-285.

Kim, T., Lovell, D., & Park, Y., 2007. Empirical Analysis of Underlying Mechanisms and Variability in Car-Following Behavior. *Transportation Research Record*, *1999*, 170-179.

Lenne, M.G., Beanland, V.C., Salmon, P.M., Filtness, A., Stanton, N.A., 2013. Checking for trains: an on-road study of what drivers actually do at level crossings. *Rail Human Factors: Supporting Reliability, Safety and Cost Reduction*, 53-59.

Liu, Y.C. and Wen, M. H., 2005. Comparison of head-up display (HUD) vs. head-down display (HDD): Driving performance of commercial vehicle operators in Taiwan. *Int. J. Human-Comput. Studies*, *vol. 61, no. 5,* 679–697.

Ma, X., & Andreasson, I., 2006. Estimation or Driver Reaction Time from Car-Following Data. *Transportation Research Record*, *1965*, 130-141.

Manstetten, D., Krautter, W., Schwab, T., 1997. Traffic Simulation Supporting Urban Control System Development. *Transportation Research Record.*

NHTSA, 2014. A Compilation of Motor Vehicle Crash Data from the Fatality Analysis Reporting System and the General Estimates System. *Traffic Safety Facts 2012*.

Panwai, S., & Dia, H., 2005. Comparative Evaluation of Microscopic Car-Following Behavior. *IEEE Transactions on Intelligent Transportation Systems*, *6*, 314-325.

Punzo, V., & Simonelli, F., 2005. Analysis and Comparison of Microscopic Traffic Flow Models with Real traffic Microscopic Data. *Transportation Research Record*, *1934*, 53-63.

Punzo, V., Formisano, D., & Torrieri, V., 2005. Nonstationary Kalman Filter for Estimation of Accurate and Consistent Car-Following Data. *Transportation Research Record*, *1934*, 3-12.

Salmon, P., Lenne, M., Young, K., & Walker, G., 2013. An on-road network analysis-based approach to studying driver situation awareness at rail level crossings. *Accident Analysis and Prevention*, *58*, 195-205.

Santos, J., Merat, N., Mouta, S., Brookhuis, K., & Waard, D. D., 2005. The interaction between driving and in-vehicle information systems: Comparison of results from laboratory, simulator and real-world studies. *Transportation Research Part F: Traffic Psychology and Behaviour*, *8*, 135-146.

Soccolich, S., Blanco, M., Hanowski, R., Olson, R., Morgan, J., Guo, F., Wu, S., 2013. An analysis of driving and working hour on commercial motor vehicle safety using naturalistic data collection. *Accident Analysis and Prevention*, *58*, 249-258.

Soria, I., Elefteriadou, L., & Kondyli, A., 2014. Assessment of car-following models by driver type and under different traffic, weather conditions using data from an instrumented vehicle. *Simulation Modelling Practice and Theory*, *40*, 208-220.

Wege, C., Will, S., & Victor, T., 2013. Eye movement and brake reactions to real world brake-capacity forward collision warnings - A naturalistic driving study. *Accident Analysis and Prevention*, *58*, 259-270.

Xu, Z., Yang, X., Zhao, X., Li, L., 2012. Differences in Driving Characteristics between Normal and Emergency Situations and Model of Car-Following Behavior. *Journal of Transportation Engineering*, *138*, 1303-1313.

Young, K., Salmon, P., & Cornelissen, M., 2013. Distraction-induced driving error: An on-road examination of the errors made by distracted and undistracted drivers. *Accident Analysis and Prevention*, *58*, 218-225.

Roadway segment image is courtesy of GoogleEarth©, retrieved July 23rd, 2014.