

## Initial Analyses from the SHRP 2 Naturalistic Driving Study: Addressing Driver Performance and Behavior in Traffic Safety

### DETAILS

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SHRP 2 Safety Project S08

# **Initial Analyses from the SHRP 2 Naturalistic Driving Study**

## **Addressing Driver Performance and Behavior in Traffic Safety**

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## CHAPTER 1

### Introduction

The second Strategic Highway Research Program (SHRP 2) is conducting the largest and most comprehensive naturalistic driving study (NDS) ever imagined. The study recruited 2,800 volunteer drivers, ages 16–80, across six sites: two counties surrounding Tampa, Florida; ten counties in central Indiana containing Indianapolis; Erie County, New York containing Buffalo; four counties in North Carolina containing Raleigh, Durham, and Chapel Hill; ten counties in central Pennsylvania containing State College; and four counties in Washington containing Seattle. All of their trips are recorded for 1 to 2 years. Data include vehicle speed, acceleration, and braking; all vehicle controls; lane position; forward radar; and video views forward, to the rear, and on the driver’s face and hands. When complete in early 2014, the NDS data set will contain over 33,000,000 travel miles from over 3,800 vehicle-years of driving, totaling over four petabytes of data.

In parallel, the Roadway Information Database (RID) will contain detailed roadway data collected on approximately 12,000 centerline miles of highways in and around the study sites plus additional information about crash histories, traffic and weather conditions, work zones, and active safety campaigns in the study areas. The NDS and RID data can be linked to associate driving behavior with the roadway environment.

Campbell (2012) provides an excellent overview of the study. Additional details may be found at the study websites [www.shrp2nds.us/](http://www.shrp2nds.us/) and <http://forums.shrp2nds.us/>.

The study’s central goal is to produce unparalleled data from which to study the role of driver performance and behavior in traffic safety and how driver behavior affects the risk of crashes. This involves understanding how the driver interacts with and adapts to the vehicle, the traffic environment, roadway characteristics, traffic control devices, and other environmental features. After-the-fact crash investigations can do this only indirectly. The NDS data record how drivers really drive and what they are doing just before the crash or near crash. The NDS and RID data will be used for years to come to develop and evaluate safety countermeasures that will prevent traffic crashes and injuries.

### The First Four SHRP 2 NDS Analyses

Four analysis contracts were awarded in 2012 under SHRP 2 Project S08, Analysis of the SHRP 2 Naturalistic Driving Study Data, to study specific research questions using the early SHRP 2 NDS and RID data. An open competition solicited proposals to address topics of the contractor’s own choosing that would have direct safety applications. The four selected contractors and their research areas are:

- Iowa State University Center for Transportation Research and Education (CTRE): Lane departures on rural two-lane curves;
- MRIGlobal: Offset left-turn lanes;

- University of Minnesota Center for Transportation Studies (CTS): Rear-end crashes on congested freeways; and
- SAFER Vehicle and Traffic Safety Centre at Chalmers University, Sweden: Driver inattention and crash risk;

The four contracts began in February 2012. In Phase 1, which concluded in December 2012, each contractor obtained an initial set of data, tested and refined their research plan, and developed a detailed plan for their full analyses. Projects selected for Phase 2 will obtain a much richer data set and complete their study by July 2014.

Summaries of each contract's Phase 1 work, prepared by the four contractors, follow. Each summary discusses:

- The research topic and why it is important;
- What is known already about the topic;
- Why NDS and RID data will provide new insights into the topic;
- The analysis plan, including what trips are analyzed and what data are needed;
- How the data were obtained from the NDS and RID data sets;
- How the work to date demonstrates that the full analyses of Phase 2 will be successful;
- Any major changes planned for Phase 2;
- What results are expected from the full analyses and how the results can be used; and
- Any lessons learned about using the NDS and RID datasets.

These summaries demonstrate how the SHRP 2 NDS and RID data can be used to address a wide variety of important highway safety research questions. They also provide examples for other researchers on effective strategies for acquiring and using these data.



## **CHAPTER 2**

# **Assessing the Relationship between Driver, Roadway, Environmental, and Vehicle Factors and Lane Departures on Rural Two-Lane Curves: An Investigation Using the SHRP 2 Naturalistic Driving Study**

Shauna Hallmark (Center for Transportation Research and Education at Iowa State University) and Dan McGehee (Public Policy Center at the University of Iowa)

### **Background**

The Federal Highway Administration estimates that 58% of roadway fatalities are lane departures (FHWA 2009). Addressing lane-departure crashes is therefore a priority for national, state, and local roadway agencies. Horizontal curves are of particular interest because they have been correlated with overall increased crash occurrence. Curves have approximately three times the crash rate of tangent sections (Glennon et al. 1985). Preston (2009) reported that 25 to 50% of severe road departure crashes in Minnesota occurred on curves, even though they only account for 10% of the system mileage. Around 76% of curve-related fatal crashes are single vehicles leaving the roadway and striking a fixed object or overturning (AASHTO 2008). Curve-related crashes have a number of causes including roadway and driver factors. Degree of curve or radius of curve is the roadway factor most cited in the literature as having an impact on crash risk (Luediger et al. 1988; Miaou and Lum 1993). Other factors that have been correlated to the frequency and severity of curve-related crashes include length of curve, type of curve transition, lane width and shoulder width (Zegeer et al. 1981), preceding tangent length (Milton and Mannering 1998), presence of spirals (Council 1998), grade (Fink and Krammes 1995) and required speed reduction between the tangent and curve.

Driver error on horizontal curves is often due to inappropriate speed selection, causing an inability to maintain lane position. FHWA estimates that approximately 56% of run-off-road fatal crashes on curves are speed related. Distracting tasks such as radio tuning or cell phone conversations can draw a driver's attention away from speed monitoring, changes in roadway direction, lane keeping, and detection of potential hazards (Charlton 2007). Other factors include sight distance issues, fatigue, or complexity of the driving situation (Charlton and DePont 2007; Charlton, 2007). McLaughlin et al. (2009) evaluated run-off-road events in the Virginia Tech Transportation Institute (VTTI) 100-car study and found that distraction was the most frequently identified contributing factor along with fatigue, impairment, and maneuvering errors.

## **Project Objectives**

Because rural curves pose a significant safety problem, and the interaction between the driver and roadway environment is not well understood, the objective of this research is to assess the relationship between driver behavior and characteristics, roadway factors, environmental factors, and the likelihood of lane departures on rural two-lane curves.

In order to accomplish this, SHRP 2 NDS and RID data were used to develop initial models that explore how drivers interact with the roadway environment and what conditions are present when a driver does not successfully negotiate a curve versus what conditions are present when successful negotiation occurs. This includes the conditions of the driver, roadway, and to a limited extent, the environment. The project will gain insight into where a driver's attention is focused during curve negotiation and what roadway cues are the most effective in keeping drivers within their lane.

Most highway agencies are proactive in implementing a range of countermeasures to reduce lane departures on curves and other areas. However, agencies have only limited information about the effectiveness of different countermeasures. The results of this research will provide more information about which specific roadway features are correlated to increased risk of lane departure. It will also provide valuable information about how drivers interact with roadway features and the impact that that has on the effectiveness of countermeasures. This will allow agencies to make better decisions about countermeasure selection.

## **Research Questions Addressed**

This research was tailored to address three fundamental research questions:

1. What defines normal curve negotiation?
2. What is the relationship between driver distraction, other driver characteristics, roadway characteristics, environmental characteristics and risk of lane departure?
3. What roadway cues and countermeasures are the most effective in getting a driver's attention and how do they affect driver response?

Each question addresses the problem from a different perspective and as a result a different methodology was proposed for each as described in the corresponding section.

## **Data Collection and Reduction**

In Phase 1, Florida data collection was the most advanced so the team manually identified rural curves in Florida based on information about where trips were likely to have occurred. Geographic buffers around those curves were submitted to VTTI and a total of 90 useable traces (trips) were identified in the NDS data. Roadway, environmental, and operational characteristics were extracted. A site visit was made to the VTTI secure data enclave to reduce driver glance location and distraction for each trace. In general it was determined that the data were similar to

what had been expected and that all of the variables necessary with a few minor exceptions would be available for Phase 2.

Considering the results for Phase 1, the sample size was determined for Phase 2 based on what would be needed to fully answer the research questions balanced with what could economically and feasibly be conducted in Phase 2. Although each question has slightly different data needs, the same NDS and RID data can be used to answer all three questions. The sample size for Phase 2 was based on research question 2 since it has the most covariates and will require the most data. It was estimated that around 1,000 traces would be sufficient. The driver and roadway characteristics initially determined to be the most relevant were used to construct a sampling plan with a specific focus on roadway countermeasures. Phase 2 data will focus on North Carolina, Indiana, New York, and Pennsylvania which have the most rural driving.

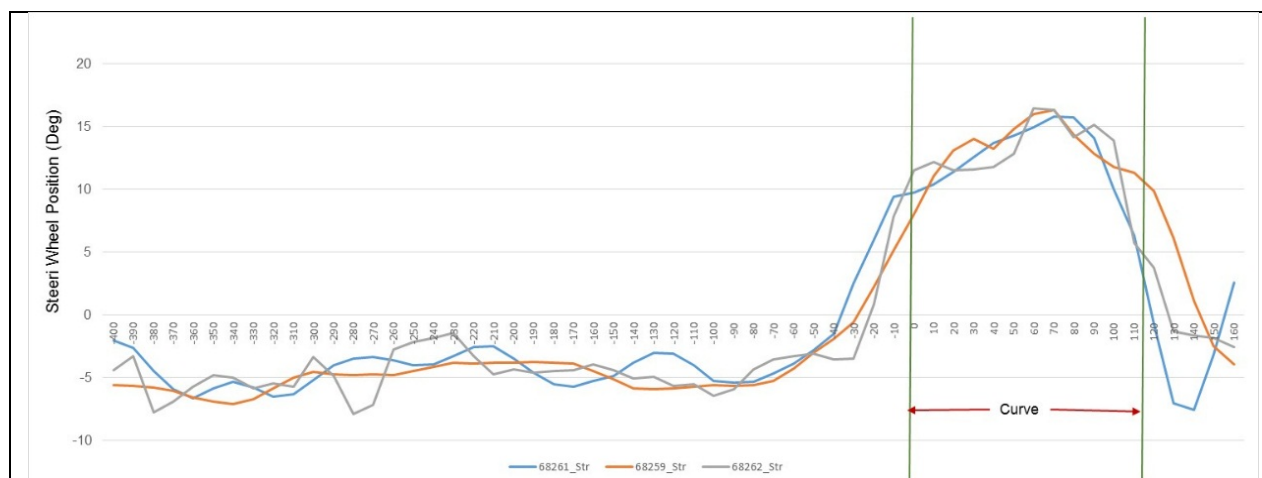
## **Crash Surrogates**

Crash surrogates are necessary to conduct both Phase 1 and Phase 2 of this research. A number of potential crash surrogates were considered against what data were available in Phase 1 and are expected to be available in Phase 2. Lane deviation, or position within the lane, was selected as the type of crash surrogate that was the most feasible given the available data and resources. Crash surrogates will be ordered by risk and boundaries developed between thresholds which will include normal driving, safety critical lane departures, near crashes, and crashes. The team used initial datasets to determine the boundary between normal driving and a lane departure event.

## **Analysis Plan**

Because three fundamental questions were addressed, a different methodology was developed specific to each. Early assessments of the data indicate that the necessary data can be extracted in Phase 2 to answer each research question and initial model results indicate that the selected models are appropriate.

Answering research question 1 entails developing a conceptual model of curve driving. The model will help identify zones where driver workload and behavior differ and assess how this affects successful curve negotiation. The model will also be used to define boundaries between lane departure events and normal driving. Times series data, at the level collected from each vehicle, will be used as the data input. The conceptual model evaluates changes in driver attention and response through curve negotiation expressed as changes in vehicle kinematics. Initial results, using a qualitative assessment, indicate that forward acceleration, accelerator pedal position, and speed showed marked changes within 200 meters upstream of a curve suggesting that this area can be used as the curve area of influence. The relationships between curve negotiation and vehicle kinematic variables, such as steering position, were assessed as shown in Figure 2.1.



**Figure 2.1. Steering wheel position for curve 503 WB.**

Research Question 2 will address how driver distraction, speeding, and other driver behaviors in conjunction with roadway and environmental factors affect the likelihood of a crash or lane departure on rural two-lane curves. Multivariate logistic regression was used to model the probability (odds) of a given type of lane departure based on driver, roadway, and environmental characteristics. Data were aggregated to the event level.

A logistic model was developed in Phase 1 using 90 events. A model was only developed for right-side lane departures since there were only five left-side lane departures in the Phase 1 data. Results indicate that the odds of a right-side lane departure are 7.1 times higher for drivers negotiating the outside of the curve than for drivers on the inside of a curve. In this model, curve direction was the only statistically significant variable. Initial results were not as good as had been expected. However, the range of characteristics evaluated was limited. Only a few curves were available in the dataset, and of the 12 drivers, only three drivers produced over 70% of the lane departures. This suggests that the likelihood of a lane departure is highly correlated to driving style and the over-representation of only a few drivers may have overwhelmed the model. This underscores the need to ensure that a large sample of drivers over a range of geometric conditions is available for Phase 2. The threshold was increased to  $-0.3$  m beyond the right edge line and a simple odds ratio found that the amount of distraction a driver was engaged in upstream of the curve was also significant.

Research Question 3 focuses more specifically on driver response to changing roadway characteristics and will be used to determine what roadway cues and countermeasures affect driver response. A time-series model will be developed which will incorporate the dynamic process of information acquisition and response as a driver negotiates a curve. This will allow the team to determine how roadway cues and countermeasures affect driver response. For example, drivers on a roadway with rumble strips may exhibit better lane keeping than drivers on a curve with similar characteristics without rumble strips.

A dynamic linear model was used to develop an initial model, which related lane offset to curve characteristics. The dynamic model form was selected because it allows for the flexibility of modeling several time series at once which will allow the team to develop estimates of what “normal driving” looks like, allowing differences in covariates or behavior when lane departures occur to be evaluated.

## **Additional Considerations for Phase 2**

A review of initial data for Phase 1 indicated that, for both the NDS and RID data, overall data quality, resolution, and format were similar in most cases to what was expected. Review of the data also suggested that more stringent thresholds need to be set for lane departure because a higher than expected number of lane departures resulted from the initial threshold of -0.1 meters beyond the lane line.

## **Lessons Learned**

A number of lessons were learned during Phase 1 which informed plans for Phase 2. The most important lesson was that the data request should be carefully constructed so that the unusable data are filtered out. For instance, it was realized that a filter should be used to exclude traces in which desired data, such as lane position, are missing. A protocol to identify unusable traces was developed to ensure that sufficient samples are available for Phase 2.

## **Translating Research to Practice**

The research will provide results that will aid transportation agencies in understanding the relationship between driver distraction and other characteristics and curve negotiation. The results will allow agencies to better understand which curve treatments result in fewer and less severe lane departures. Stakeholders who are expected to use the results include safety researchers, AASHTO, FHWA, state Departments of Transportation, counties, and cities. The research will also result in information about driver distraction that can be used by policy makers.

Most highway agencies actively implement a range of countermeasures to reduce lane departures on curves and other areas. However, only limited information is available about the effectiveness of different countermeasures. The results of this research will provide more information about which specific roadway features are correlated to an increased risk of lane departure. It will also provide valuable information about how drivers interact with roadway features and the impact that their interaction has on the effectiveness of countermeasures. This will allow agencies to make better decisions about countermeasure selection. Understanding how drivers approach the task of curve negotiation will also provide invaluable information about why certain countermeasures work. The research has implications for roadway design, selection of sign type and placement, sight distance, and selection and application of countermeasures. It is expected that more appropriate application of countermeasures to mitigate run-off-road or head-on crashes on curves will result in fewer fatal crashes.

Steps will be taken to ensure that, when appropriate, results from Phase 2 can be translated to practice. Tech briefs will be developed to summarize information about which factors are correlated to lane departures. Results about the effectiveness of different countermeasures will be included in a toolbox of curve countermeasures which the team has developed for state and county agencies. The team will communicate any information about placement or effectiveness of existing traffic control devices to the National Committee on Uniform Traffic Control Devices.

## CHAPTER 3

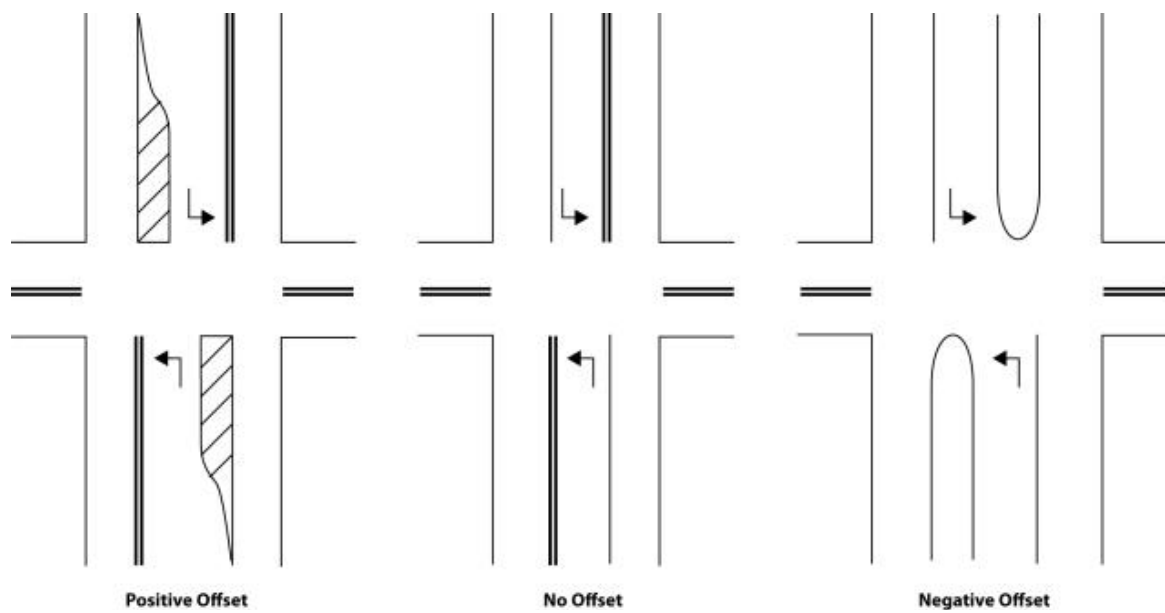
# Evaluation of Offset Left-Turn Lanes: An Investigation Using the SHRP 2 Naturalistic Driving Study

Karin M. Bauer and Jessica M. Hutton (MRIGlobal)

### Introduction

The scope of MRIGlobal's research is to determine whether data from the NDS can be effectively used to determine if offset left-turn lanes affect gap acceptance behavior and improve safety for left-turning vehicles. Results from the full analysis will provide design guidance for offset left-turn lanes that is lacking from the current AASHTO *Green Book* (AASHTO 2011) and state highway agency design manuals.

Left-turn lanes are used at intersections to provide a safe location for storing left-turning vehicles out of the through traffic lanes while their drivers wait for a suitable gap in opposing traffic to turn left. The provision of a left-turn lane minimizes the potential for rear-end collisions with through vehicles approaching from behind the left-turning vehicle and the pressure on left-turning drivers to leave an exposed position and accept an inappropriate gap in opposing through traffic. The *Highway Safety Manual* (AASHTO 2010) provides crash modification factors (CMFs) for left-turn lanes at four-leg intersections that range from 0.45 to 0.90, depending on the intersection type, area type, and number of left-turn lanes provided. However, left-turn lanes along roadways with medians may create a safety concern, as vehicles in opposing left-turn lanes may block one another's views of oncoming through traffic. A geometric design solution for the sight obstructions that can occur due to opposing left-turn vehicles is to offset the left-turn lanes (i.e., to move the left-turn lane laterally within the median so that the opposing left-turn vehicles no longer block the sight lines of their drivers). The drawings in Figure 3.1 illustrate intersections with negative offset, zero offset, and positive offset for opposing left-turn lanes.



**Figure 3.1. Illustration of positive, zero, and negative offset left-turn lanes.**  
(Persaud et al. 2009, adapted from Staplin et al. 2001)

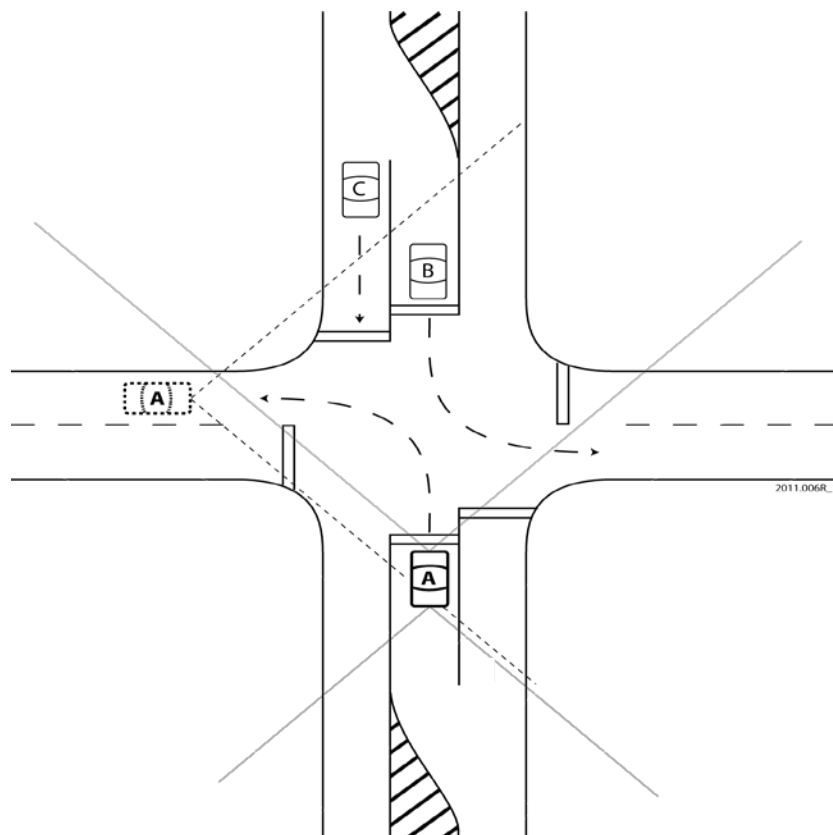
Offset left-turn lanes are used at signalized and unsignalized intersections. At signalized intersections, they are most effective when permissive-only left-turn phasing is used, since left-turning vehicles do not have to select appropriate gaps for completing their maneuvers during a protected left-turn phase. While the principle of offset left-turn lanes is accepted based on anecdotal evidence, there is no conclusive quantitative evidence of their effects on driver behavior or crash reduction.

MRIGlobal has completed a proof-of-concept study using a limited dataset from early in the collection of NDS data. The work included identifying appropriate intersections to study within the NDS areas; developing data requests and assisting in development of queries of the NDS dataset; reducing NDS video data to capture the relevant information for the analysis; and completing a preliminary analysis of the data to demonstrate the methods that would be used for a full analysis with a larger dataset.

### Working with the NDS Data

For this proof-of-concept study, NDS data were requested for left-turn maneuvers at six signalized intersections in the Raleigh/Durham, North Carolina and Buffalo, New York study areas. The dataset provided includes forward-facing and rear-facing videos, basic trip characteristics, and some time-series data for the trip segments that took place within a 1,000-ft radius of the center of the study intersections. In addition, forward-facing videos were received for all NDS study vehicles passing through one of the study intersections within the same 1,000-ft boundaries. The primary source of data for identifying rejected and accepted gaps was the videos from left-turning NDS vehicles.





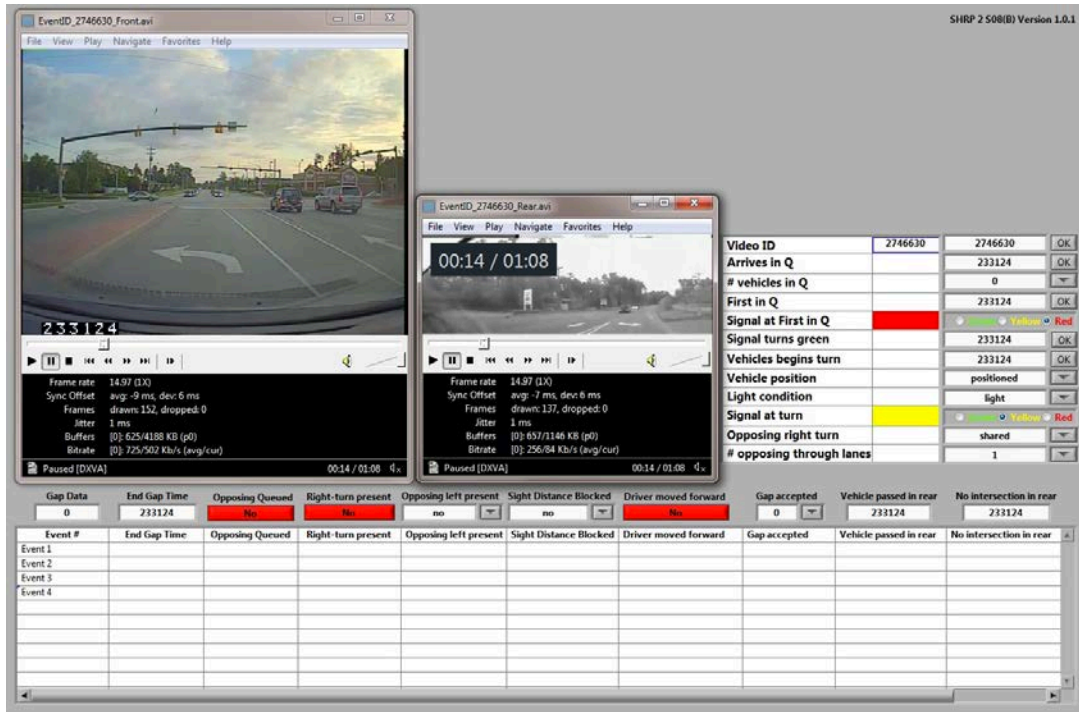
**Figure 3.2. Illustration of vehicle maneuvers at an intersection without offset left-turn lanes.**

Figure 3.2 shows a drawing of an intersection without offset left-turn lanes at which an opposing left-turn vehicle is potentially blocking the left-turning driver’s view of opposing traffic. The vehicles in the drawing are as follows:

- Vehicle A is the NDS study vehicle (the instrumentation in Vehicle A collects the data needed for this study).
- Vehicle B is making the opposing left-turn maneuver to Vehicle A.
- Vehicle C is a through vehicle on the same approach as Vehicle B; Vehicles A and C are potentially in conflict as the driver of Vehicle A considers making a left-turn maneuver; several “Vehicle Cs” may pass before the driver of Vehicle A accepts a gap and completes the left-turn.

The illustration shows the general field of view for the forward and rear camera installed in Vehicle A. The forward video was used to gather gap rejection information as Vehicle Cs passed through the intersection prior to Vehicle A accepting a gap. The rear video was used after Vehicle A completed the turn to view the next Vehicle C to pass through the intersection, allowing the analyst to record the length of the accepted gap. In addition to gathering this

information for Vehicle A, the gap acceptance behavior of vehicles queued in the left-turn lane ahead of Vehicle A can typically be observed in Vehicle A's forward-facing camera. These data were also recorded during the data reduction process.



**Figure 3.3. Screenshot of prototype user interface developed by MRIGlobal in Phase 1.**

A user interface (Figure 3.3) was designed using LabView software to simplify the data reduction process and ease workload for the analyst. The key characteristics of the interface include:

- Automatic population of video file name;
- One-click procedure for recording the timestamp of events of interest;
- Drop-down menus or buttons to present available event codes to the analyst;
- Population of default values where appropriate, so if no change is needed, the analyst can skip the variable field; and
- Intuitive design and layout.

## Preliminary Analysis

Table 3.1 presents a summary of the data that were reduced from video files. Distributions of rejected and accepted gaps are shown in Figure 3.4, separately for the three types of offset. A basic logistic model was developed using the data (a) combined across the three offset types and (b) using offset type as a factor to illustrate the methodology proposed in the Phase 1 work plan. The modeling results are illustrated in Figure 3.5 without regard to offset type (left) and using

offset type as an analysis factor (right). Each plot shows the functional form that relates the probability of accepting a gap and that gap's length. From the model represented on the left-hand side plot in Figure 3.5, the research team then estimated the critical gap length,  $T_{50}$ , at which the probability of accepting a gap is equal to that of rejecting it. The estimated  $T_{50}$  is 7.8 sec with a 95-percent confidence interval of 7.1 to 8.8 sec. The plot on the right-hand side in Figure 3.5 illustrates the probability curves when using offset type as a factor in the modeling. The analysis of variance associated with this logistic model did not show a significant offset effect. This was expected because the data are based on only six intersections, only one of which has a negative offset. In summary, because of the limited amount of data available in this project, no conclusions could be drawn yet regarding the safety impact of offset left-turn lane design. However, the team met the project goal of showing that the analysis could be accomplished using the NDS dataset.

**Table 3.1. Data Captured in Phase 1**

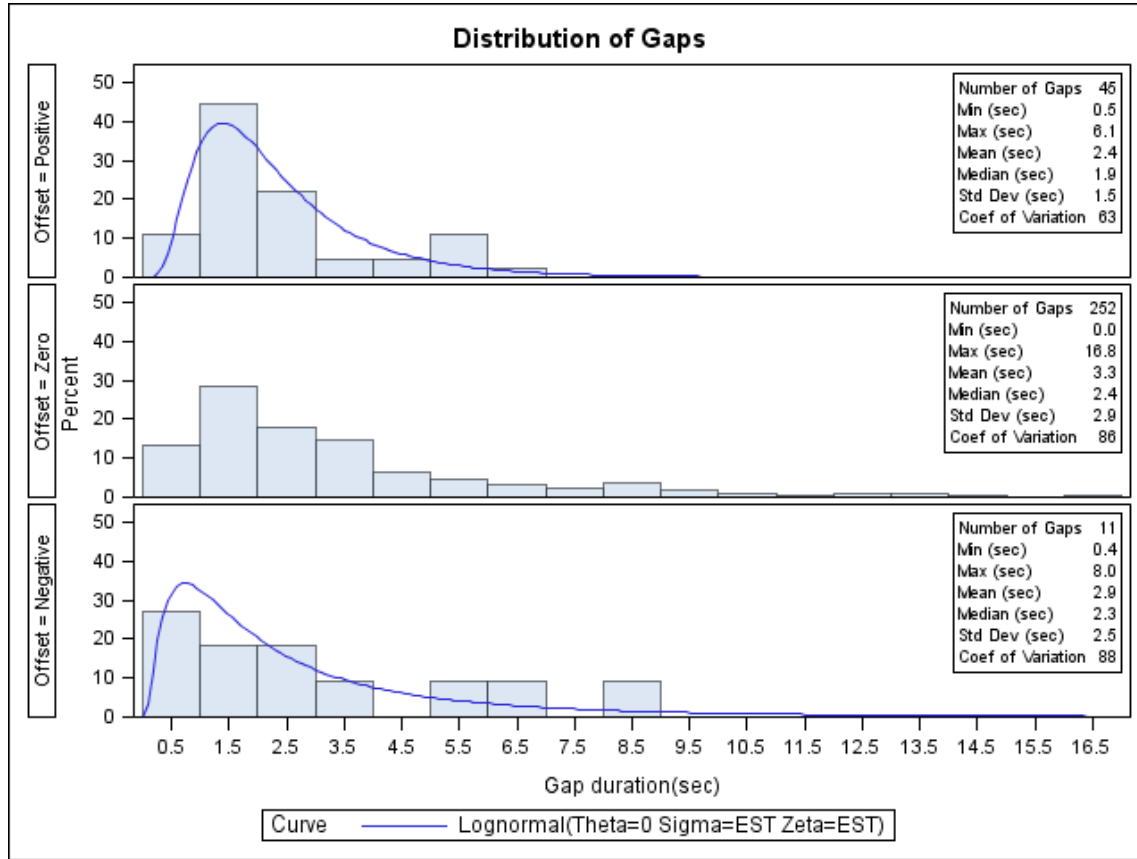
Unique object ID (VTI)	Offset type	Number of left-turn maneuvers recorded		Total number of rejected gaps	Total number of accepted gaps	Number of events with a vehicle present in the opposing left-turn lane	
		NDS vehicles	Non-NDS vehicles			No	Yes
7	Positive	9	2	39	2	20	21
13		1	0	4	0	4	0
19	Zero	32	10	87	10	61	36
23		25	1	34	2	31	4
28		23	14	104	15	81	20
33	Negative	3	0	10	1	11	0
<b>Total</b>		<b>93</b>	<b>27</b>	<b>279</b>	<b>30</b>	<b>208</b>	<b>81</b>

## Plans for Phase 2

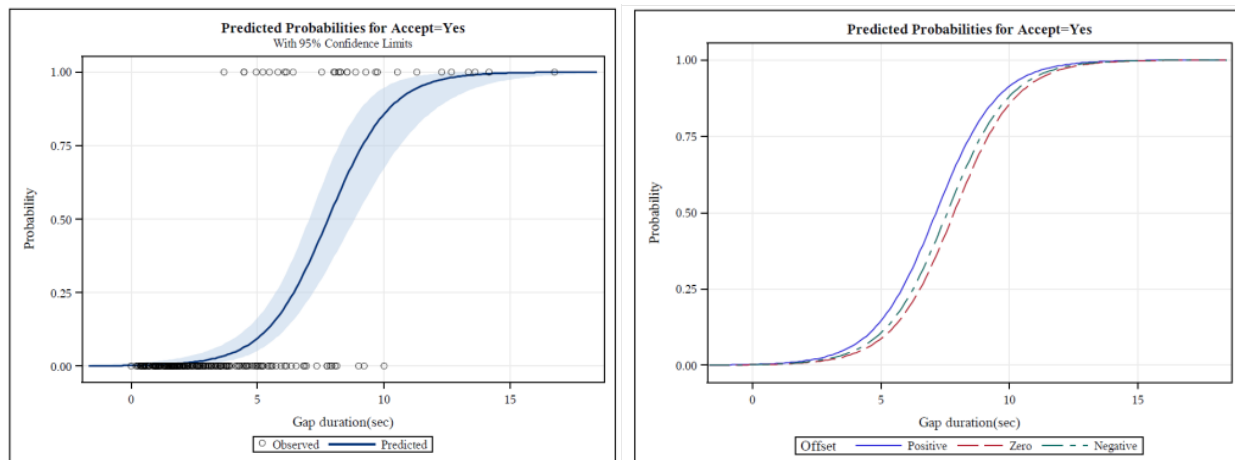
In Phase 2, the research team plans to increase the sample size by using a dataset of approximately 70 intersections, and to categorize the intersections by offset distance (likely a 3-ft to 4-ft range) as well as offset type. It is anticipated that the 70 intersections will yield between 2,500 and 4,000 trip segments, or left-turn movements completed by NDS study drivers, for analysis. In addition, each trip segment may also include observations of left-turn maneuvers made by non-NDS study vehicles for which gap acceptance can be observed. In turn, each left-turning vehicle will yield up to several rejected gaps and one accepted gap (if it can be observed or estimated from the video data). Based on the small sample in Phase 1 that included just a few months of NDS trip data, it is estimated that the full Phase 2 study, which will include at least three times as many NDS driver trips, may yield in the order of 8,000 rejected gaps and 1,000 accepted gaps.

With this dataset, the team will be able to determine if offset left-turn lanes affect driver gap acceptance behavior, as well as whether the presence of a vehicle in the opposing left-turn lane has an impact on the effect. The research will provide design guidance for offset left-turn lanes that is lacking from the current AASHTO Green Book (AASHTO 2011) and state highway agency design manuals. The interpretation of the research results from Phase 2 will establish a

minimum desirable offset for opposing left-turn lanes and determine how that information can best be presented as design guidance for application by intersection designers. This should have a direct impact on fatal and injury crashes that involve left-turn maneuvers, as well as on many less severe crashes.



**Figure 3.4. Distribution of gaps by left-turning study vehicles.**



**Figure 3.5. Probability of accepting a gap as a function of gap duration--offset types combined (left) and by offset type (right).**

## **CHAPTER 4**

# **Car Following, Driver Distraction, and Capacity-Reducing Crashes on Congested Freeways: An Investigation Using the SHRP 2 Naturalistic Driving Study**

Gary A. Davis, John Hourdos, and Indrajit Chatterjee (University of Minnesota)

### **Introduction**

It has been estimated that about 50% of the congestion experienced on urban roadways is due to nonrecurring causes, with capacity-reducing incidents being responsible for about 25% (FHWA 2012). One prominent type of incident is the freeway rear-ending crash. Although these crashes result in serious injuries on occasion, they also generate substantial social costs through delays imposed on other freeway users by reducing available freeway capacity at critical times. Reducing the frequency of these crashes should help achieve better use of an increasingly strained urban freeway system. At present, however, there is a shortage of countermeasures that have been proven effective in reducing freeway rear-ending crashes, although a range of potential countermeasures are currently being considered.

Empirical evidence indicates that freeway rear-ending crashes tend to occur when stopping waves form on freeways, while a theoretical analysis suggests that the occurrence of “critical events,” in which following drivers brake at rates substantially higher than their leaders, should play an important role in determining whether stopping waves result in crashes. This is because harder braking by a following driver tends to reduce the stopping distance available to the follower’s followers, making avoidance of a crash successively more difficult (Brill 1972). An important insight from Brill’s model is the relationship among reaction time, following headway, and safe braking rate. Drivers whose reaction times exceed their following headways need to brake harder than their leaders, while drivers whose following headways exceed their reaction times can brake more gently.

### **Proposed Analysis**

The SHRP 2 NDS offers a unique and potentially powerful source of data relevant to understanding driver behavior in the field, and the goal of this project is to advance the understanding of how drivers behave when confronted with a freeway stopping wave. This will be done by extracting from the NDS a sample of relevant events and then reducing the data for these events to produce estimates that characterize the situations confronting drivers as well as their reactions to these situations. This reduced dataset will then be used to address three general questions:

1. What is the role of drivers’ allocation of attention—especially of potentially distracting activities—in determining whether or not a braking event is critical?

2. What is the potential for an idealized driver-assist system to reduce the likelihood of critical events?
3. What impact on driver behavior would an idealized roadway-based system need to achieve to realize a target reduction in the likelihood of critical events?

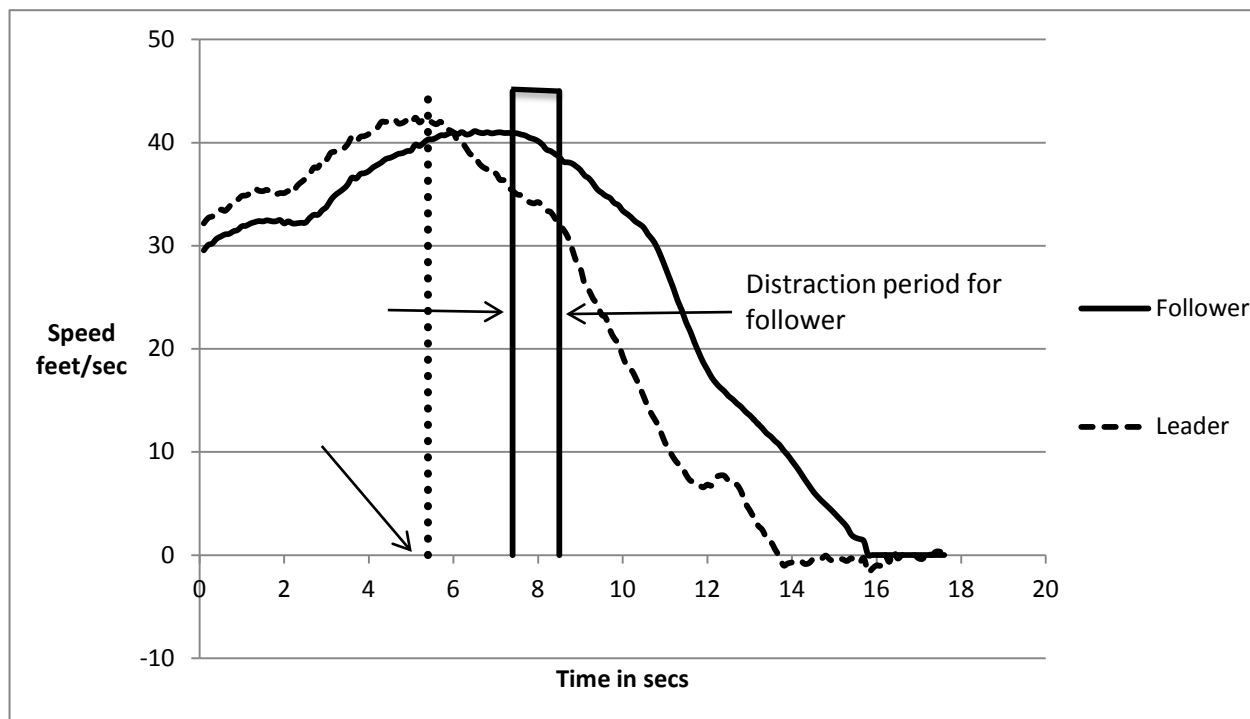
## **Phase 1 Objectives**

During Phase 2 the research team proposes to construct, from the NDS, a dataset of approximately 250 freeway trips containing brake-to-stop events. Using NDS radar, speedometer, forward video, and GPS data, the team will then compute estimates of features such the initial speeds of the NDS vehicle and its leader, the braking decelerations used by the two drivers, and the follower's reaction time and following distance. The work during Phase 1 focused on four questions related to the feasibility of this plan:

1. Can freeway brake-to-stop events be identified efficiently from the NDS database?
2. Can the NDS in-vehicle video be used to characterize driver actions and identify intervals of possible distraction?
3. Can quantitative features of brake-to-stop events be estimated from the NDS time-series data?
4. What types of analyses can be conducted using the resulting dataset?

## **Phase 1 Accomplishments**

To address question 1, after identifying locations and times where the Seattle freeway system was likely to be congested, the team obtained from VTTI 214 useable trip segments satisfying the team's time and space constraints. Manual study of the forward-facing video and time-series data revealed that 14 of these trips contained events in which the instrumented vehicle braked to a full or near stop. Using this as a learning sample, the team then explored different screening procedures aimed at automatic identification of brake-to-stop events. A simple screening based on a speed threshold was able to eliminate all but 33 of the non-braking trips, while retaining the 14 braking trips. A more sophisticated algorithm was able to eliminate all non-braking trips while retaining 13 of the 14 braking events.



**Figure 4.1. Speeds of a leading and following vehicle versus time, showing the time point at which the leader began braking and the time interval during which the follower looked down to adjust a radio.**

To address question 2, characterization of driver behavior before and during braking events, one of the team members spent two days at VTTI's secure enclave, where he viewed the video for 20 events, including the 14 braking events identified earlier. It was not only possible to classify potentially distracting activities but also, via the video frame time stamps, to determine when and how long the distracting activities occurred and to relate these intervals to the NDS time-series data.

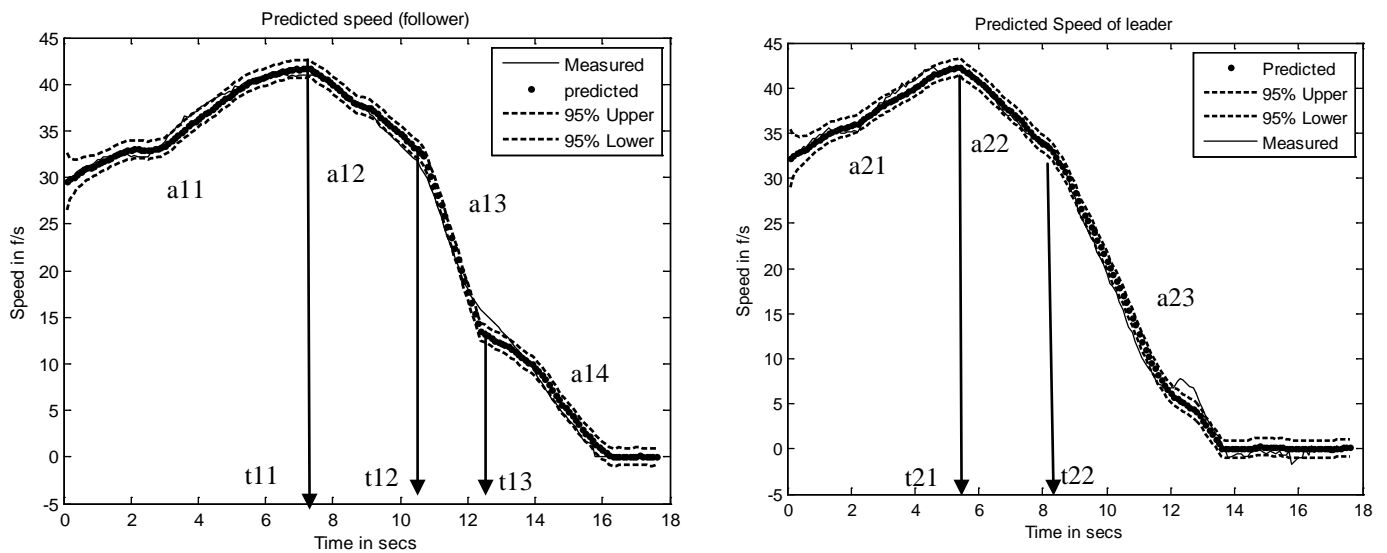
Figure 4.1 illustrates the integration of different NDS data types. Figure 4.1 plots the speeds of the leading and following vehicles as constructed from NDS time-series data, the point at which the leading vehicle's brake lights went on as observed in the NDS forward-camera video, and a period of apparent distraction by the following driver obtained by observing the NDS face video.

Question 3 is concerned with computing quantitative estimates of features such as reaction time, braking rates, and speeds. The research team developed a two-level approach to reducing and analyzing the NDS data. In the first and simpler level, each braking event was described using six elements: the initial speeds of the leading and following drivers, the follower's headway and reaction time, and the average decelerations used by the leader and the follower. The team developed a spreadsheet tool to compute the first-level estimates of the six elements from inputs obtained from the NDS forward video and time-series data. The second level of reduction and analysis involved replacing the average deceleration rates of the first level

with more detailed estimates of the acceleration/deceleration sequences used by the leader and the follower. This was done through detailed modeling of the leader and follower trajectories, using the NDS forward radar, speedometer, and GPS speed time-series data.

**Table 4.1. Estimates of Braking Sequences for the Leading and Following Vehicles Depicted in Figure 4.2**

Leader		Follower	
Time (seconds)	Acceleration (ft/sec <sup>2</sup> )	Time (seconds)	Acceleration (ft/sec <sup>2</sup> )
0	1.8 (a21)	0	1.4 (a11)
5.4 (t21)	-3.2 (a22)	7.4 (t11)	-2.7 (a12)
8.3 (t22)	-5.8 (a23)	10.8 (t12)	-10.8 (a13)
		12.4 (t13)	-3.15 (a14)



**Figure 4.2. Graphic display of leader and follower speeds, along with braking sequences from Table 2.**

Table 4.1 gives the estimated sequence of braking rates for the leader and follower shown in Figure 4.1, while Figure 4.2 is a graphic display of these results. The leader was initially accelerating at about 1.8 ft/sec<sup>2</sup>; at about time 5.4 seconds, the leader began decelerating at about -3.2 ft/sec<sup>2</sup>; and at time 8.3 seconds, the leader increased deceleration to about -5.8 ft/sec<sup>2</sup>. The follower was initially accelerating at about 1.4 ft/sec<sup>2</sup>; at time 7.4 seconds, the follower began decelerating at -2.7 ft/sec<sup>2</sup>; and at time 10.8 seconds, the follower increased deceleration to about -10.8 ft/sec<sup>2</sup>. The follower’s period of apparent distraction shown in Figure 4.1 immediately preceded the leader’s increase in deceleration, and the time between the leader’s increase in deceleration and the response by the follower was a relatively long 2.5 seconds.

Finally, to address question 4, the team prepared a small (24 event) example representing the dataset the team plans to construct. This example dataset was used to illustrate how one could determine if potentially distracting activities on the part of a following driver were risk factors



for that driver causing a critical event, and to illustrate how cluster analysis can be used to classify the elements characterizing braking events. Regarding possible countermeasures, the example dataset was used to predict the effect a vehicle-based countermeasure might have on the incidence of critical events, and to estimate specifications or constraints that a road-based countermeasure would need to satisfy to achieve a target change in the likelihood of critical events.

## Conclusion

Rear-ending crashes on congested freeways are responsible for a significant fraction of the nonrecurring delays that are becoming regular features of urban travel, and reducing the frequency of these crashes should lead to better use of our increasingly strained freeway system. At present, there is a shortage of countermeasures that have been proven effective in reducing freeway rear-ending crashes, but it is becoming clear that the key is to understand how drivers respond to the occurrence of stopping waves. An important class of events, which the team calls critical events, are those in which a following driver brakes at a significantly higher rate than his or her leader. Even when the following driver is not involved in a crash, this sort of event can establish conditions that make a crash later in the stopping wave more likely. The study's goal is to compile, from the NDS, a dataset of brake-to-stop events on freeways and use this dataset to investigate relations between the conditions that make rear-ending crashes more likely and how drivers distribute attention between driving and non-driving tasks. The bulk of the effort during Phase 1 was devoted to demonstrating the feasibility of this plan by (1) developing and testing triggers for identifying brake-to-stop events from NDS time-series data, (2) developing and testing a method for characterizing drivers' allocation of attention from the NDS face video, and (3) developing and testing methods for estimating quantitative features of brake-to-stop events. The Phase 1 work then illustrated how the proposed dataset could be used to identify distraction as a risk factor for critical events, how cluster analysis could be used to classify brake-to-stop events, and how the proposed dataset could be used to do first-cut estimates of the effectiveness of a vehicle-based driver-assist system and a road-based driver warning system.

## CHAPTER 5

# Safer Glances, Driver Inattention, and Crash Risk: An Investigation Using the SHRP 2 Naturalistic Driving Study

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### Introduction

Driver inattention is a long-standing major factor related to fatality in motor vehicle crashes (Evans 2004). It is also a flourishing problem associated with the communication, information, and entertainment technology that is transforming the car and modern portable technology such as the smartphone (NHTSA 2010a). In 2009 distraction was involved in crashes causing 5,474 deaths and leading to 448,000 traffic injuries across the United States (NHTSA 2010b). Consequently, there is a critical need to better understand distraction and the limits of attention while driving.

Driver inattention is very high on the national traffic safety agenda (see [www.distraction.gov](http://www.distraction.gov)). There is an increasing amount of legislation, regulation, design guidelines, and information campaigns related to driver inattention. The vehicle and electronics industries are moving fast to respond to both enable the use of electronic functionality in a safe manner and to reduce driver inattention through safety systems which are capable of monitoring it.

Two main developments have combined in the past few years to create this escalation: (1) there is a growing concern over the driving-compatibility of the ever-increasing functionality available through electronic devices (such as smartphones and intelligent vehicle systems), and (2) research has been showing a much clearer association between driver inattention and crash risk.

### State of the Art on Dangerous Glance Behavior

The specific mechanisms and indicators of the risk of inattention are not definitively quantified. The main source of a clearer association between driver inattention and crash risk has been naturalistic driving studies such as the 100-car study (Dingus et al. 2006). Initial analyses have been able to identify the crash risk associated with distracting *activities* or tasks, such as texting, dialing, and eating; however this approach does not explain why the tasks are dangerous nor provide the objective inattention performance information needed for guidelines and inattention countermeasures while driving.

Subsequent analyses of the 100-car eyeglance data show that high total glance times (e.g., 2 seconds or more in a 6 second period) are associated with increased crash/near-crash risk (Klauer et al. 2006; 2010). Liang, et al (2012) compared 24 different ways to combine various glance characteristics, such as single glance duration, glance history, and glance location. They

found that single off-road glance duration was the best crash predictor. Glance history (such as total glance time) and glance location did not improve risk estimation above single glance duration but they were still predictive of crash/near-crash risk.

Further analyses of the 100-car data have revealed that risk is pinpointed to the timing of off-road glances in relation to external events. Risk is primarily associated with an inopportune single glance duration (Victor and Dozza 2011; Victor, Dozza, and Lee, forthcoming). The most sensitive measures for risk are those which most precisely quantify an off-road glance that overlaps a change in the state of environment or action that began the sequence leading the crash or near crash called the precipitating event (e.g., a lead vehicle that begins braking). The longer the driver looks away from the road at this specific time, the greater the risk.

## **Naturalistic Driving Data and Validated Inattention Crash Risk**

Naturalistic driving data is valuable in comparison to driving simulator and field experiments (see NHTSA 2012) because it is able to quantify real crash risk. However, previous naturalistic data have been limited by the number of crashes collected and by the quality of data (e.g., radar data).

The SHRP 2 naturalistic data can provide the data that is needed to achieve validated inattention performance measures associated with pre-crash situations. The data are essential to improve the understanding of driver inattention, for guidelines to reduce distraction from electronics devices, for countermeasures that detect and act to reduce distraction while driving, and for regulation and education.

## **Analysis Plan**

This research seeks to develop a statistically validated set of inattention-risk functions (or relationships) describing how an increase in inattention performance variables in lead-vehicle pre-crash scenarios leads to increased risk. Likewise, these relationships identify which glance behaviors are safer than others.

The events needed for this analysis are lead-vehicle crashes, near crashes and associated comparison conditions (baselines). The key data needed for each event are eyeglance variables, variables that describe the visual information that drivers rely on to initiate and control braking (called optical parameters), and measures of event severity, or how serious a crash or near crash is.

The analysis plan is devised as an extension of work that has been done previously by the researchers in this project (Liang et al, 2012; Victor and Dozza, 2011; and Jonasson and Rootzén, forthcoming) on the 100-car dataset. These previous analyses provide the requirements for the analysis plan, including a data-driven sample size assessment. The plan is adaptive to accommodate data and sample size limitations.

The analysis plan is formulated in five analytic steps. Each analytic step is expected to provide better precision and explore different components of the inattention-risk relationship by providing more detail on inattention-risk relationships under different circumstances –

relationships to timing with optical parameters, glance characteristics, and relationships with respect to different levels of crash severity. In fact, each of the analytic steps provides one or more inattention-risk functions for each step of the analysis. No major changes are planned for Phase 2.

The analysis starts with Step 1, which replicates and extends previous research. The results of Step 1 represent an improvement over previous work because they identify a more precise relationship between glance patterns and crash risk for the specific rear-end pre-crash scenarios.

Step 2 places these glance patterns and their associated odds ratios in the context of a theoretical explanation of how particular glance patterns increase crash risk: the sweet spot. The (perceptual motor) sweet spot indicates the time when perceptual information is particularly valuable in crash avoidance and when a glance away from the road would be particularly risky.

Step 3 integrates the glance measures, such as duration of glances away from the road that overlap the sweet spot, as well as other measures such as the glance history.

Step 4 builds on Step 3 by quantifying the injury severity associated with a crash and so creates a more precise assessment of inattention-related risk. Each of the preceding analytic steps represents contributing components, together building a more precise inattention-risk relationship. Step 4 relates glance behavior to injury severity as defined by new severity scales. High severity crashes represent more likely loss of life and disabling injuries: the ultimate risk posed by distraction.

Step 5 highlights the importance of going beyond a simple inattention-risk function to consider inattention-risk relationships, represented here as a set of inattention-risk functions. Step 5 provides a family of statistical relationships that indicate crash likelihood or injury severity given contextual characteristics of the crash situation, such as traffic density, road type, and speed.

When integrated, the five analytic steps provide more precise knowledge about the relationship between inattention and risk than each of these components separately. This approach will deliver progressively more precise inattention-risk functions (or relationships) at each analytic step. This approach is therefore also adaptive to the outcomes of the analyses, as it can stop when further analysis does not provide “stronger” inattention-risk relationships or when the sample size does not permit the analysis. For example, if the sample size is sufficiently large it is possible to analyze the inattention-risk relationship in different conditions of traffic density, road types, speed, and distraction types.

Each analytic step provides an important component that will contribute to an increasingly better understanding of the relationship between inattention and risk of crashes and the severity of the associated injuries.

## Data

In total, 13 events were obtained from the NDS database: 4 rear-end crashes, 5 near crashes, and four baseline events. Three crashes were found because they were reported. One crash and all the four near crashes were found using a  $-1g$  acceleration trigger. The four baselines were selected randomly from the same trips where the crashes occurred. The baselines were selected to match the criteria that there should be a lead vehicle present and that the driver's vehicle should be moving a majority of the time.

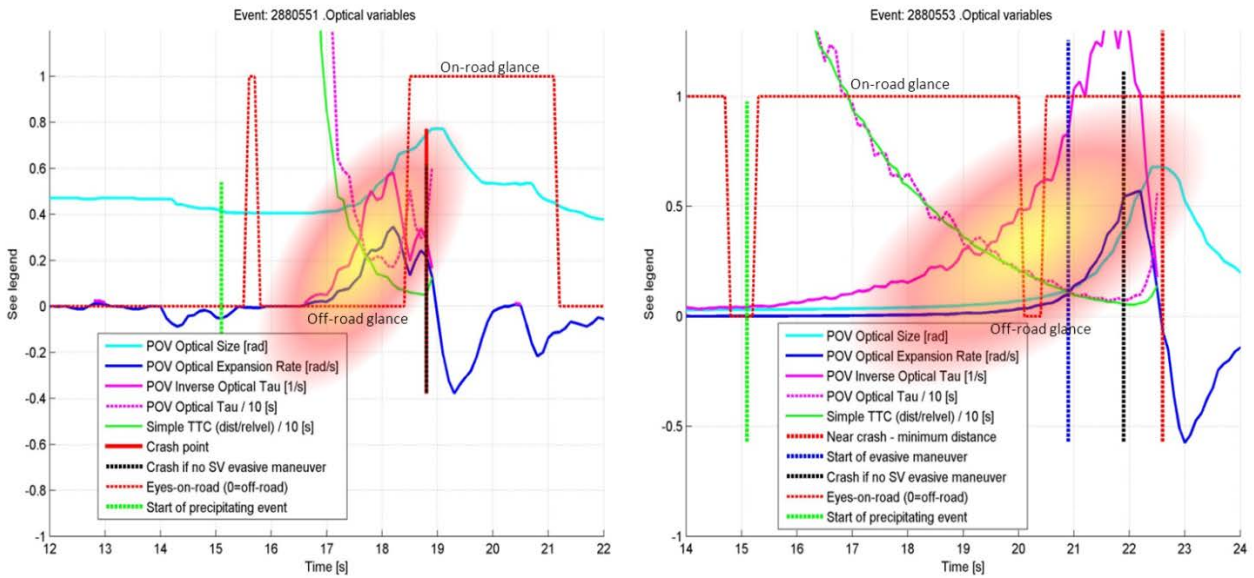
The main data used are glance variables (total glances, overlapping glance, last glances, and total preceding glances), optical parameters (optical size and expansion rate of the lead vehicle, and Tau, which is a combination of the two), and two measures of event severity (calculated from time-to-collision, relative speed, the mass of vehicles involved, start of an evasive maneuver, or when there would be a crash).

## Results

All variables that were needed to be able to conduct the analyses as defined in the analysis plan above were successfully calculated for the 13 events. Data quality difficulties were overcome. For example, an approach to use lead vehicle size coding from video to fill out the gaps in the radar data provided good range and range-rate data for crashes (where the data were often missing close to crash). The main lesson learned was that video has proven to be extremely useful for understanding and validating many measures, but most importantly for filling in radar data gaps.

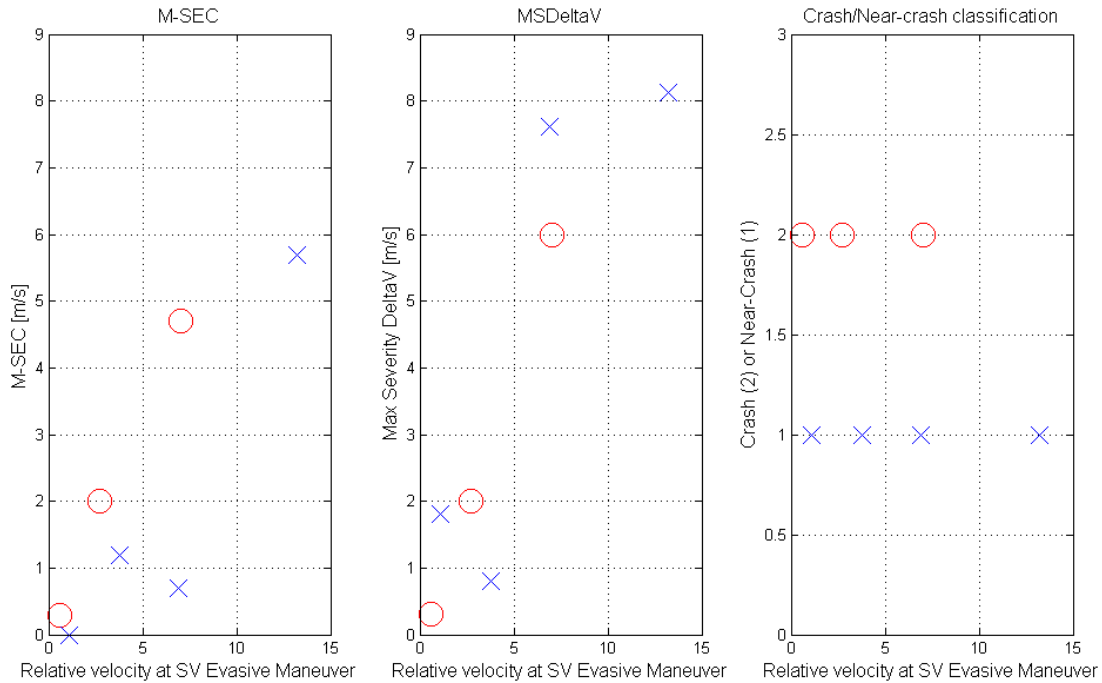
For the *replication* analysis, aggregated glance data plots show results that are in line with expectations (the 100-car data). They demonstrate a technical realization that improves upon previous methods by including a longer period that includes crash points.

For the *sweet spot* analysis, the optical parameters were successfully objectively quantified from radar and video data (see Figure 5.1). Further case studies, plotting the glances in all events in relation to inverse Tau, show an improvement upon previous methods by realigning data to the crash point and minimum distance. Data also show that there may be a difference in glance behavior between crashes and near crashes.



**Figure 5.1. Optical variables for one crash event (2880551) on left, and one near-crash event (2880553) on right. A hypothetical spatio-temporal sweet spot is illustrated with heat maps.**

The *glance characteristics* analysis focused on an analysis of whether glances could be automatically calculated by using the head tracker sensor data. The analysis showed clearly that it is not recommended. The head tracking is often lost, and when data is available, it is often erroneous or misleading. Manually reduced eyeglances are on the other hand highly reliable, feasible, and efficient.



Note: Crashes = O; near crashes = X.

**Figure 5.2. The three types of severity measures M-SEC, MSDeltaV, and the SHRP 2 event severity variable.**

Two new scalar *severity measures*, M-SEC and MSDeltaV, were implemented as an alternative to the traditional severity-categorical approach (Figure 5.2). Plots of the scales reveal examples of how near crashes can be more severe than crashes, demonstrate the implementation feasibility, and how the scales can be better suited for statistical analyses.

As the last step, an expression of the *set of inattention-risk functions* was developed:

$$P_i(\text{Severity} \mid \text{Context}) = F_i(\text{Sweet Spot}, \text{Glance Characteristics})$$

where  $i$  denotes different sets and combinations of *Context* parameters such as *traffic density*, *road type*, *SV speed* and *distraction type*. Different contexts will provide different probability functions.

Further, two approaches (Extreme Value Theory and Context Dependent Risk) were developed to make it possible to extrapolate from behavior in near crashes to crashes, and from less severe crashes to more severe ones. Extreme Value Theory is also used to detect and correct for the selection biases in the data.

## Expected Results and Implications for Countermeasures

The *main scientific result* of this research is a quantitative relationship between inattention and risk. A *set of inattention-risk functions*, or family of statistical relationships, will provide more

precise knowledge as a whole than individually. This research will identify a more precise relationship between glance patterns and their associated risk around a sweet spot, a time when perceptual information is particularly valuable in crash avoidance. Further, it will relate glance behavior to injury severity as defined by new severity scales. This set of functions will indicate crash likelihood and/or injury severity for certain contextual characteristics of the lead-vehicle crash scenario, such as traffic density, road type, and speed.

These relationships can be used to show more precisely which glance behaviors are safer than others. For example, this research can be used to show how much the risk of a serious injury can be reduced when tuning a radio by changing the series of single glances to be shorter, and can relate this net benefit to a potential cost of increasing the number of glances needed to finish tuning the radio. It can determine how this risk varies with different types of contexts (e.g., stop-and-go versus free-flowing traffic), can determine the point in time where the eyes are needed most for the control of braking, and can be used to understand the type of glance behavior that leads to crashes as opposed to near crashes.

Safer glance strategies for interacting with electronics and the traffic environment can be encouraged in a number of ways including design guidelines, education, and in-vehicle feedback. Likewise, the most dangerous glances can be pinpointed and associated with improvements to appropriate countermeasures such as distraction guideline performance criteria and active safety system technology.

These results can address current limitations in scientific knowledge regarding *driver distraction guidelines* for in-vehicle electronic devices. More evidence is needed to provide valid assessment and compliance criteria for performance testing. Project results can be used to support evidence-based distraction policy and regulations, and can be used to teach safe glance behaviors.

Systems that detect inattention while driving are highly prioritized for *intelligent vehicle safety systems* (NHTSA 2010a). This research will improve safety systems such as Forward Collision Warning Systems to make them inattention-adaptive. It will reduce nuisance warnings and warn more exactly when the risk is greatest. Further, this research will greatly improve how distraction and inattention is detected because the inattention-risk functions directly describe what a system should be looking for. Distraction feedback and warnings can more appropriately be given and driver coaching feedback is improved.



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