

Modeling Slow Lead Vehicle Lane Changing

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(ABSTRACT)

Driving field experiment data were used to investigate lane changes in which a slow lead vehicle was present to: 1) characterize lane changes, 2) develop predictive models, and 3) provide collision avoidance system (CAS) design guidelines. A total of 3,227 slow lead vehicle lane changes over 23,949 miles were completed by sixteen commuters. Two instrumented vehicles, a sedan and an SUV, were outfitted with video, sensor, and radar data systems that collected data in an unobtrusive manner.

Results indicate that 37.2% of lane changes are slow lead vehicle lane changes, with a mean completion time of 6.3 s; most slow lead vehicle lane changes are leftward, rated low in urgency and severity. A stratified sample of 120 lane changes was selected to include a range of maneuvers. On the interstate, lane changes are performed less often, $t(30) = 2.83$, $p = 0.008$, with lower urgency ratings, $F(1, 31) = 5.24$, $p = 0.05$, as compared to highway lane changes, as interstates are designed for smooth flow. Drivers who usually drive sedans are more likely to make lane changes than drivers of SUVs, $X^2(1) = 99.6247$, $p < 0.0001$, suggesting that driving style is maintained regardless of which experimental vehicle is driven.

Turn signals are used 64% of the time but some drivers signal after the lane change starts. Of cases in which signals are not used, 70% of them are made with other vehicles nearby. Eyeglance analysis revealed that the forward view, rearview mirror, and left mirror are the most likely glance locations. There are also distinct eyeglance patterns for lane changing and baseline driving. Recommendations are to use forward view or mirror-based visual displays to indicate presence detection, and auditory displays for imminent warnings.

The “vehicle + signal” logistic regression model is best overall since it takes advantage of the distance to the front and rear adjacent vehicle, forward time-to-collision (TTC), and turn signal activation. The use of additional regressors would also improve the model. Five design guidelines are included to aid in the development of CAS that are useable, safe, and integrated with other systems, given testing and development.

DEDICATION

This effort is dedicated to my uncle, Phil Olsen, who encouraged me to consider doctoral work; my grandfather, Charles Telford, whose clocks continue to tick-tock each day; my mother, Janet Telford, for her encouragement and editorial advice; my father Richard Olsen, who ventured into the world of accident analysis, prevention, and human factors research long before I had an inkling of what such work was; and Larissa and her Larissa-friendly world.

Finally, this effort is dedicated to everyone who has ever suffered as a result of a traffic incident of any type; it is hoped that this document may contribute in some small way toward the end of such suffering.

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STANDARD NOMENCLATURE

AADT	Average Annual Daily Traffic (a measure of traffic volume)
AFCCF	Average Fraction Correctly Classified for Fit
ANOVA	Analysis of Variance
CAS	Crash Avoidance System
Dist1	“Distance one” refers to the distance from the Subject Vehicle (SV) to the slow Principal Other Vehicle (POV) ahead
Dist2	“Distance two” refers to the distance from the SV to the approaching POV in the rear adjacent lane behind the SV
DV	Dependent Variables
ΔV	Delta-V or relative velocity
F	Forward (glance) or Female
FARS	Fatal Accident Reporting System (by NHTSA)
FAZ	Fast Approach Zone
ft/s^2	Feet per second squared
HUD	Head-up Display
I-81	Interstate 81 (an interstate route in southwest Virginia)
IC	Instrument Cluster (glance)
IND	Indeterminate (glance)
IV	Independent Variable(s)
LBS	Left Blind Spot
LC	Lane Change
LCAS	Lane Change Crash Avoidance System
LM	Left Mirror (glance)
LW	Left Window (glance)
M	Male
\bar{M}	Mean
mph	miles per hour
m/s^2	Meters per second squared
N	Number of experimental participants, items, or cases
n	Number of observations
NHTSA	National Highway Traffic Safety Administration
OINT	Other Interior (glance)
OLR	Ordinary linear regression
p	Probability
\hat{P}_i	The estimated probability value of a lane change
$1 - \hat{P}_i$	The estimated probability value of a baseline event
POV	Principal Other Vehicle (vehicle near SV)
PZ	Proximity Zone
Rads	Radians
R	Rear
RBS	Right Blind Spot
RM	Right Mirror (glance)
RW	Right Window (glance)

RVM	Rear View Mirror (glance)
s	Seconds
SAS	SAS Institute, Inc. (statistical analysis software)
<i>SD</i>	Standard Deviation
Sed	Sedan
SedDrv	Sedan Driver (usual vehicle driven)
SUV	Sport Utility Vehicle
SUVDrv	SUV Driver (usual vehicle driven)
SV	Subject Vehicle (experimental vehicle)
Sync	Synchronization Number (time stamp)
TTC	Time-To-Collision
TTC1	“TTC one” refers to the TTC with the slow lead vehicle.
TTC2	“TTC two” refers to the TTC with a POV approaching the SV from the rear adjacent lane.
t_0	Time zero (lane change start point)
χ^2	Chi-square Goodness of Fit
US 460	United States Route 460 (a highway route in southwest Virginia)
VDOT	Virginia Department of Transportation
VTI	Virginia Tech Transportation Institute
y_i	Indicates the result is a lane change (1 for lane change)
$1 - y_i$	Indicates the result is a baseline event (0 for baseline)

GLOSSARY

Average Annual Daily Traffic (AADT): A measure of traffic volume used by the Virginia Department of Transportation.

Average Fraction Correctly Classified for Fit (AFCCF): A measure of the logistic regression model's ability to match the existing data. The AFCCF is used in a manner similar to the R^2 statistic in linear regression to compare several competing models, in that the closer to 1.0, the better the fit.

Baseline: Straight-ahead driving events to which lane-changing events were compared.

Blind Spot: Area associated with a direction to the rear of the Subject Vehicle, associated with the rear adjacent lane. Typically this area is not visible within the left side mirror and requires a head turn to confirm that it is clear for a safe lane change to occur.

Crash Avoidance System (CAS): An in-vehicle integrated system of sensors and displays that can issue alerts when a potentially dangerous situation is present. A lane-change CAS (LCAS) monitors rear areas to provide information to the driver about vehicles approaching in the adjacent lane.

Destination Lane: The lane into which the lane change is made. For lane change to the left, the destination lane would be the left lane for a 2-lane road. See also End Point.

Duration: Refers to the time required to complete a lane change. Duration is calculated by subtracting the end synch number from the start synch number.

End Point: End of the lane change, indicated by a “settling” in the new lane. This point would be after any lane overshoot and is defined in terms of motion relative to the lane boundaries. It is the point when the vehicle’s lateral velocity relative to the lane is below a threshold for a specified period of time. End point is generally determined visually as the point at which the vehicle is centered in the new lane. See Destination Lane and Initiation Point.

Experimental Vehicle: Experimental vehicle driven by the participant. Both a sedan and an SUV were driven by all participants.

Eye Glance Position: The position to which the driver is looking. Discrete positions include center-forward, left-forward, right-forward, right mirror, left mirror, rearview mirror, right window, left window, right blind spot, left blind spot, instrument cluster, other interior, and indeterminate.

Fast Approach Crash: A case in which there is a longitudinal gap between vehicles prior to the start of the lane change; this gap is closed at a substantial velocity differential between the two vehicles. Typically, this is the case in which a vehicle from behind is approaching a vehicle ahead that attempts a lane change into the path of the approaching vehicle.

Fast Approach Zone (FAZ): The area in the adjacent lane from 30 to 162 feet behind the rear bumper of the Subject Vehicle (SV). See also Rear Adjacent Lane and Severity Rating.

First Lateral Movement: Associated with the initiation or start of a lane change (t_0), indicating the first movement from the original lane toward the destination lane. Usually determined visually, based on video data review.

Frequency: Refers to the number of lane changes completed, given a certain length of time or distance. Frequency is likely influenced by lane choice, velocity, and traffic density.

Head-up Display (HUD): A HUD is a virtual visual display or image that is visible directly ahead of the driver and could include alerts or other information such as velocity, indicator status, component settings, and warnings.

Headway: Refers to the forward area between a lead vehicle and a following vehicle, in time or distance. For this dissertation, time headway (i.e., the elapsed time between the front of the lead vehicle passing a point on the roadway and the *front* of the following vehicle passing the same point) is used. Headway = Range/Velocity of the following vehicle. Headway may also refer to the time between the Subject Vehicle (SV) and the closest forward vehicle in the destination lane, or the time between a following vehicle in the destination lane and the SV ahead of it.

Initiation Point. The point marking the beginning of a lane change, representing the decision point (go/no-go) at which the driver decided to begin the lane change maneuver. In some cases, it can be defined by a combination of criteria, including a return fixation to the forward location, steering wheel movement, turn signal activation, lateral vehicle movement toward the destination lane boundary, and lane departure. In most cases, the first lateral movement toward the new destination lane can be used to identify t_0 . Initiation Point is also referred to as time zero (t_0) or start point.

Lane Change: A deliberate and substantial shift in the lateral position of a vehicle, usually from one lane into another.

Lane Change Crash Avoidance System (LCAS): A CAS that monitors rear areas to provide information to the driver about vehicles approaching in the adjacent lane.

Lane Change Duration: See Duration, the time required to complete a lane change.

Lane Change Latency: Also referred to as Latency. Refers to the time period before lane change initiation (t_0) during which specific behaviors can be observed. Lane Change Latency is also the 3-second time period before t_0 , during which specific eye behaviors can be observed.

Large Set: The entire set of 3,227 slow lead vehicle lane changes.

Multiple Lane Change: More than 1 lane change completed in the same direction (i.e., crossing multiple lanes of traffic). A multiple lane change is a lane change in which one or more lanes are

crossed over, such as a lane change from the right lane, across the center lane, into the left lane on a three-lane roadway.

Original Lane: The lane from which the lane change originates. For lane change to the left, the original lane would be the right lane for a two-lane road. See also Initiation Point or Start Point.

Passing Maneuver: A maneuver consisting of two single-lane changes that takes place in less than or equal to 45 seconds, such as changing lanes from the right lane to the left lane and then back into the right lane to pass a slow lead vehicle.

Principal Other Vehicle (POV): Surrounding vehicles that are likely influential on the Subject Vehicle (SV), such as a slow lead vehicle or vehicle in the rear adjacent lane approaching the SV (e.g., to pass the SV on the left).

Proximity Crash: A case in which there is little or no longitudinal gap and the velocity differential between vehicles is small. This is the most frequently occurring lane change crash.

Proximity Zone (PZ): The area in the adjacent lane from 4 feet in front of the bumper of the Subject Vehicle (SV) to 30 feet behind the rear bumper of the SV. This area generally includes the blind spot and the area beside and behind the vehicle in which another vehicle is likely to travel. See also Rear Adjacent Lane and Severity Rating.

National Highway Traffic Safety Administration (NHTSA): A federal agency under the U.S. Department of Transportation. NHTSA is responsible for reducing deaths, injuries, and economic losses resulting from motor vehicle crashes. NHTSA is the sponsor of this research.

Radians: A unit of plane angular measurement determined by the requirement that there are two rads in a circle. Two rads = $360/\pi$ degrees. This means that one rad = $180/\pi$ degrees, and one degree = $\pi/180$ rads. Since $\pi/180$ = approximately 0.017, one degree = approximately 0.017 rads, three degrees = 0.052 rads, 12 degrees = 0.209 rads, and so on. The position of the steering wheel and the Principal Other Vehicle (POV) position are measured in rads (azimuth).

Range: The distance from the front bumper of the following vehicle to the rear bumper of the lead vehicle. For this dissertation, this is the distance from the Subject Vehicle (SV) to the slow lead vehicle in the same lane or to the closest forward vehicle in the destination lane, or the distance from the front bumper of the closest rear vehicle in the adjacent lane to the rear bumper of the SV, along a longitudinal axis through either of the vehicles.

Range-rate: The rate at which the range between two vehicles is changing. Range-rate is measured in terms of relative velocity (ΔV), in which the velocity of one vehicle is subtracted from the velocity of the other vehicle. Range-rate will be of concern in terms of distance to the slow lead vehicle, distance to the vehicle in the forward adjacent lane, and distance to an approaching vehicle in the rearward adjacent lane.

Relative Velocity: The difference between velocities of two vehicles. See also *Range-rate*.

Rear Adjacent Lane: The lane directly next to (i.e., adjacent to) the lane in which the Subject Vehicle (SV) is present and a Principal Other Vehicle (POV) is located to the rear of the SV. For left lane changes, the POV would be in the rear adjacent lane prior to SV lane change initiation. The rear adjacent lane is associated with the Fast Approach Zone and Proximity Zone as well.

Sample Set: The sample set of 120 slow lead vehicle lane changes selected from the large set.

Sedan Driver: A driver who normally drives a sedan as his or her regular commute vehicle. This is one of two classifications of Usual Vehicle.

Severity: The severity rating scale reflects conflict aspects of vehicle movement, where conflict is associated with vehicles in the adjacent lane when the driver of the Subject Vehicle (SV) moves into that lane. Severity is a seven-point severity rating scale (1 = unconflicted, 7 = physical contact) indicating the degree to which the vehicle in the destination lane was cut off. Severity is used for rating lane changes. Severity was rated based on vehicle presence within the Proximity Zone (PZ) (4 feet in front of the Subject Vehicle to 30 feet behind it) and time-to-reach the rear edge of the PZ for those vehicles within the Fast Approach Zone (FAZ) (30 to 162 feet behind the SV). A severity level of 7 pertains to physical contact between vehicles and level 6 pertains to emergency or unplanned maneuvers required to avoid a collision. Levels 1 through 5 of the rating scale are related to other vehicles in the PZ (level 5), or within the FAZ and their relationship to the end of the PZ (levels 1 through 4). See Table 3.5.

Sensitivity: The probability of correctly classifying a lane change, when it is indeed a lane change. It is calculated by dividing $\sum_{i=1}^n y_i \hat{P}_i$, the sum of all y_i s, times their respective estimated probabilities associated with a lane change, by $\sum_{i=1}^n y_i$, the sum of all y_i s.

Single Lane Change: A lane change consisting of a single movement from one lane into another, such as from the right lane into the left lane on a two-lane roadway. See Passing Maneuver.

Slow Lead Vehicle: The Principal Other Vehicle (POV) forward of the Subject Vehicle (SV), which is typically slower than the SV, causing the lane change.

Slow Lead Vehicle Lane Change: This type of lane change refers to a lane change that is made, in which a principal other vehicle (POV) ahead is moving at a speed slower than the subject vehicle (SV) making the lane change. The maneuver begins with the first lateral movement toward the lane line and ends when the vehicle has settled in the destination lane.

Specificity: The probability of correctly classifying a baseline event, when it is indeed a baseline event. It is calculated by dividing $\sum_{i=1}^n (1 - y_i)(1 - \hat{P}_i)$, the sum of all $1 - y_i$ s, times their respective estimated probabilities associated with baseline events, by $\sum_{i=1}^n (1 - y_i)$, the sum of all $1 - y_i$ s.

Start Point: Start of the lane change, defined predominantly by first lateral movement of the vehicle toward the new destination lane. See *Initiation Point*. Also referred to as Start Sync or End Sync, indicating the sync number associated with the start or end of the lane change. Referred to as t_0 (time zero).

Subject Vehicle (SV): The vehicle making the lane change. For this dissertation, the SV is the instrumented vehicle.

SUV Driver: A driver who normally drives a SUV, van, or pick-up truck as his or her regular commute vehicle. One of two classifications of Usual Vehicle.

Sync Number: The synchronization number or time stamp visible on the video data to which other data files were tied. Sync used time as an anchor and was recorded in tenths of a second.

Time to Collision (TTC): Time required for two vehicles to collide if they continue on at their present speed and path (McLaughlin, 1998). $TTC = \text{range}/\text{range-rate}$.

Time Stamp: See Sync Number.

Unsuccessful Lane Changes: An aborted lane change, unintentional lane change, or partial lane change, usually involving the case in which the vehicle does not completely change lanes intentionally. An aborted lane change is one that is begun but not completed (e.g., a lane line crossing). An unintentional lane change may be the result of an internal distraction, such as reaching for a cellular phone or other object within the vehicle. A partial lane change is one in which a lane change is begun to avoid an object on the side of the road, but which does not consist of changing into another lane completely. Unsuccessful lane changes are quite rare.

Urgency Rating. Lane change urgency was rated on a four-point scale (1 = not urgent, 4 = critical) that indicated how soon the lane change was needed, based on TTC with the closest vehicle ahead (or behind for vehicles such as tailgaters in the same lane or others in the rear adjacent lane). Has an inverse relationship with TTC (i.e., a low TTC indicates a high urgency rating). See Table 3.6.

Usual Vehicle: Refers to the type of vehicle usually driven; that is, the vehicle that the driver normally drives. A sedan driver is one who normally drives a sedan as his or her regular vehicle day-to-day, under non-experimental conditions. An SUV driver is one who normally drives and SUV (or similar vehicle) as his or her normal or usual vehicle.

Vehicle Position: The position of vehicles surrounding the SV, in terms of in front of the SV, forward of the SV in the adjacent lane, next to the SV in the adjacent lane, and rearward of the SV in the adjacent lane. See Rear Adjacent Lane.

Validation Set: The set of 85 lane changes used to validate the candidate logistic regression models.

CHAPTER 1: INTRODUCTION

This document describes research performed to analyze lane change data that was based upon data collected via a previous effort conducted by the experimenter. The six main sections include the introduction, literature review, method, analysis and results, discussion and conclusion, and design guidelines. A glossary, reference list, and numerous appendices are also included.

The introduction serves to define and identify the lane change, specify the objectives of this study, and list research questions. A literature review then provides a survey of related research and summarizes the data needed, as identified within the literature. The method section describes the experimental methods used in three phases: data collection, maneuver identification and categorization, and data sample categorization. The procedure is described for each of these phases as well. The analysis and results section outlines the analysis for all data and for a sample of data, and discusses model and development. A discussion and conclusion section provides an interpretation of the results and highlights the most relevant discoveries. Five design guidelines are presented as a stand-alone document, offering guidance for designing crash avoidance systems.

The Crash Problem

As a result of motor vehicle crashes, property is damaged, and people are delayed, injured, or killed each year. The first recorded motor vehicle incident occurred on September 13, 1899, when Henry H. Bliss was struck by an automobile in New York City (“Fatally Hurt,” 1899). In the year 2000, nearly 6.4 million U.S. motor vehicle crashes were reported to the police --that is one crash every five seconds. Of these crashes, there is an average of one person injured every 10 seconds, and a fatality occurs every 12 minutes (National Highway Traffic Safety Administration [NHTSA], 2002a). Of reported crashes, the annual death toll is over 40,000 people, and 3.1 million people are injured each year. According to one estimate, the cost of these crashes is over \$150 billion annually (NHTSA, 2001). There has been an increased need for improved driver safety since that first automobile fatality in 1899. In the U.S., more than three million cumulative traffic fatalities have been recorded, as well as billions of injuries. Worldwide, it is estimated that 30 million people have been killed in traffic accidents to date (Walk Sacramento, 2002).

A large portion of each year’s motor vehicle fatalities are related to fatality factors such as running off the road and failure to keep in the proper lane. A recent query of NHTSA’s Fatal Accident Reporting System (FARS) Web-Based Encyclopedia (NHTSA, 2002b) revealed that, out of the total number of vehicle fatalities, in 2002 there were 18,782 lane/road departure fatalities out of a total 42,815 crash fatalities. That is, of the number of accidents that had a fatality, “running off road” or “failure to keep in proper lane” showed up as a factor in the accident report, as filled out by the reporting officer (C. L. Van Dan Elzen, personal communication, September 6, 2003). This accounts for over 43% of the vehicle fatalities. These factors can be addressed by a lane change collision avoidance system.

A subset of these crashes is categorized specifically as lane-change crashes. These crashes occur when a driver is in the process of maneuvering the vehicle laterally from one lane into another. Transportation researchers estimate that lane change crashes account for between 4 and 10% of all crashes (Barr & Najm, 2001; Eberhard et al., 1994; Wang & Knippling, 1994; Young, Eberhard, & Moffa, 1995). Annually, between 240,000 and 610,000 lane change crashes are reported to the police. In these reported lane-change crashes, at least 60,000 people are

injured and a significant amount of property is damaged (Barr & Najm, 2001; Najm & Smith, 2002; NHTSA, 2001; Wang & Knipling, 1994). It is also estimated that 386,000 unreported lane change crashes occur each year (Chovan, Tijerina, Alexander, & Hendricks, 1994; Wang & Knipling, 1994). Lane change crashes account for between 0.5 and 1.5% of all motor vehicle fatalities, or 224 to 732 fatalities per year (NHTSA, 2001; Wang & Knipling, 1994).

Overall, lane-change crashes account for a relatively small percentage of all fatalities (0.5%) and a relatively large percentage of all police reported crashes (4%). Another measure of the cost of crashes, is in terms of Fatal Crash Equivalents (FCE), a weighted measure relating the cost of all crashes to the cost of one fatal crash of a particular type. In terms of FCE, lane change crashes account for a moderate percentage of the injury and trauma, loss of life, property damage, and other costs (1.4%) (Wang & Knipling, 1994; Young, Eberhard, & Moffa, 1995). In addition, crashes associated with lane changing account for almost 10% (41.2 million hours) of all crash-caused delay, primarily due to the high probability of multiple lane blockages when such crashes occur (Chovan et al., 1994).

Most crashes are attributed to driver error and inattention, rather than to failures in the vehicle or roadway. For over 50 years, at least 90% of crashes have been attributed to driver error (McFarlane & Moore, 1957). Wang, Knipling, and Goodman (1996) concluded that over 25% of crashes involved inattentiveness as a causal factor. For lane change crashes, the issue seems to be much the same. Research has revealed that most drivers in lane change crashes did not attempt an avoidance maneuver; this finding suggests that the drivers did not see or were unaware of the presence of another vehicle or crash hazard (Chovan et al., 1994; Eberhard et al., 1994; Tijerina, 1999). According to Knipling (1993), 75% of lane-change/merge crashes involve a recognition failure by the driver. To reduce lane change crashes, drivers must be made aware of impending hazards before initiating a lane change (Chovan et al., 1994; Tijerina, 1999).

In-vehicle technology is a logical choice to assist drivers in maintaining awareness and reducing crashes. Lane-change crashes have been targeted as a prime candidate for the use of technology. It is believed that this technology would help reduce the occurrence of these types of crashes (Wang & Knipling, 1994). The use of a crash avoidance system (CAS) has been proposed. The CAS would help to alert drivers and reduce lane change crashes (Eberhard et al., 1994; Talmadge, Dixon, & Quon, 1997). A CAS is an in-vehicle, integrated system of sensors that detect hazards, and displays to issue alerts or warnings when a potentially dangerous situation is present. A lane change CAS (LCAS) extends the ability of the driver by monitoring the surrounding areas and providing information to the driver about vehicles approaching from the rear adjacent lane. The driver can respond to the LCAS alert and react as needed when preparing to make a lane change. The net result would likely be a reduction in both the occurrence and the severity of lane-change crashes; for crashes that did occur, impact speeds and resulting injuries would be reduced (Knipling, 1993). Figure 1.1 shows conceptually the reduction of both crash incidence and crash severity that could result from implementing crash reduction technology. Recent advances in sensor technologies, computer components, and digital processing have led to the potential of developing low-cost CAS to be used on vehicles (Barickman & Stoltzfus, 1999; Eberhard et al., 1994).

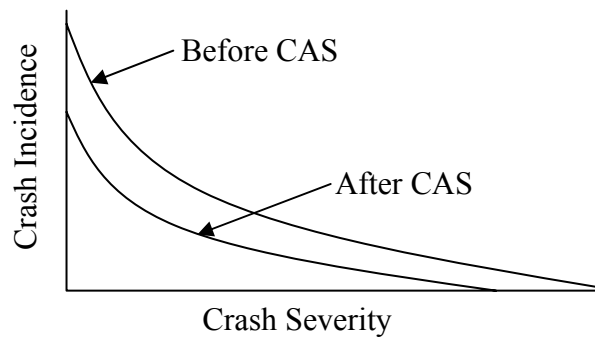


Figure 1.1. Reduction of Crash Incidence and Crash Severity (Knippling, 1993).

This dissertation focuses on understanding the period prior to initiation of a lane change, referred to as lane change latency, or simply, latency. Latency is defined as “the quality or state of being latent,” in which latent refers to something that is “capable of becoming though not now visible, obvious, or active” (Merriam-Webster, 2002). For purposes of discussion, latency refers to the period before lane change initiation, during which specific behaviors can be observed.

Lane-change crashes account for a relatively small percentage of all traffic related crashes and associated delay, property damage, injuries, and fatalities. However, focusing on lane-change crashes and the driver behaviors leading to them is a worthy effort for several reasons. Understanding must be acquired in order to design usable, safe CAS that will fit well with drivers’ behaviors and expectations. In addition, the focus on understanding lane change behavior prior to initiation may lead to developments that could be applied not only to LCAS but also to other systems. For example, common technologies may be applied to the backing, lane-change, run-off-the-road, and rear-end crash problems (Dingus et al., 1997; Knippling, 1993; Tijerina, Hendricks, Pierowicz, Everson, & Kiger, 1993; Tijerina, Jackson, Pomerleau, Romano, & Petersen, 1995). These developments could be used for a variety of contexts, environments, vehicles, and drivers, to reduce many of the costs associated with traffic crashes. Finally, techniques used to understand lane changing behavior could be applied to other crash problem areas to reduce driver errors and crashes of all types.

Limitations of Previous Lane Change Efforts

Numerous factors are relevant to changing lanes and passing while driving. Research aimed at identifying and quantifying these factors has been conducted over the past 35 years. However, these data collection efforts have had limitations including: (1) the use of obtrusive equipment, (2) the presence of an experimenter, (3) the collection of data over a short period, and (4) the limitations of controlled settings that prevent generalization of results.

The use of obtrusive equipment, such as eye-markers, helmets, and large visible video cameras (e.g., Burger, Mulholland, Smith, Sharkey, & Bardales, 1980; Godhelp, 1985; Mourant, Rockwell, & Rackoff, 1969; Robinson, Erickson, Thurston, & Clark, 1972) may constrict driver behavior by making the driving task unnatural. In most studies, an experimenter accompanied the driver and gave driving instructions during data collection (e.g., Bhise et al., 1981; Hetrick, 1997; Robinson et al., 1972; Tijerina, Garrott, Glecker, Stoltzfus, & Parmer, 1997). It is believed that the presence of an experimenter may influence driver behavior, resulting in unnatural

driving behavior. In addition, many studies of lane changing have been conducted during a single day, over only a short duration (e.g., 1.5 hours) (Hetrick, 1997; Tijerina et al., 1997; Van Winsum, De Waard & Brookhuis, 1999). Findings from these studies have provided insight but may not include a range of behaviors representing normal driver variability. Certain studies were conducted in highly controlled, somewhat unrealistic settings. For example, in an investigation of the effects of traffic on lateral head movements for left lane changes, participants followed a pick-up truck and made lane changes when the experimenter in the lead vehicle activated the turn signal (Bhise et al., 1981). While useful timing and head movement information was collected, these data may be limited to controlled, vehicle-following situations. Other lane-change research has been conducted using test tracks or constrained routes. For example, Talmadge, Chu, and Riney (2000) investigated the amount of lead time that drivers would prefer for receiving a warning when making a lane change. These data were collected while driving on a test track and on local freeways. Studying driving in these contexts can provide valuable insight. But again, both the constraint of having an observer present and the need for route control may limit the ability to generalize any findings.

Robinson, Erickson, Thurston, and Clark (1972) concluded that natural measurements taken without the driver's awareness ought to be considered for studying driving behavior (i.e., visual search). This conclusion was supported later by Chovan et al. (1994), who stated that data are needed on normal lane change times and their distribution. Likewise, Staplin, Lococo, Sim and Gish (1998) and Tijerina et al. (1997) recommended that data could be gathered under a wide range of natural driving conditions using unobtrusive observation. More recently, Tijerina (1999) suggested that studies of "plain old driving" are needed to understand lane changing, including on-road studies with instrumented vehicles and non-obtrusive video surveillance.

This dissertation describes just such a data collection effort, in which a large database of driving maneuvers has been assembled, based on a field experiment in which driving behavior data were collected in a realistic, on-road setting. It addresses Tijerina's (1999) suggestion by describing a secondary data analysis of a subset of lane-change data collected during an on-road field experiment.

Objectives

For the purposes of this effort, the context to be investigated was lane changing while driving on the freeway or highway. Specifically, the objectives of this effort were: 1) to characterize normal lane changes in which a slow lead vehicle was present, 2) develop predictive models distinguishing baseline (straight-ahead) driving from lane changes, and 3) provide design guidelines relevant to the issuing of lane change collision warnings.

The following research questions address the objectives of this dissertation, based on each research objective:

Research Questions

To address the three objectives of this research, the following research questions were derived:

Characterizing Slow Lead Vehicle Lane Changes

1. How are differences in dependent measures (e.g., lane change duration, severity, urgency) influenced by each level of independent variable (i.e., route, usual vehicle, gender, and experimental vehicle) at each level?
2. How are values for dependent measures distributed, such as for range and time-to-collision (TTC)?
3. What is the role of acceleration among vehicles?
4. What is the use and timing of turn signals?
5. For eye glance movement, what is the pattern, timing, and probability of glances?

Model Development

1. How can lane changes be predicted?
2. What variables are relevant for developing predictive models?

Guideline Development

1. Where should CAS displays be located?
2. What is the recommended timing and duration of warnings?
3. What role should turn signal indicators play?
4. Upon what criteria could predictive models be created to discriminate baseline driving from lane changing?
5. How can lane change CAS be integrated with other CAS?

Characterization involves identifying the initiation point at which the vehicle starts to move laterally into the destination lane. Distributions from a sampling of maneuvers were identified relative to this point. These distributions include range and TTC to surrounding vehicles, such as the slow lead vehicle, and the closest rearward vehicle in the destination lane. The use of turn signals has been described in terms of timing and frequency of use. Eye movements leading up to lane-change initiation were also analyzed. In addition, distributions were identified for lane-change frequency and duration, and vehicle velocity. Comparisons and statistical analysis were completed with regard to route, usual vehicle (i.e., the vehicle normally driven by the participant), gender, and experimental vehicle. These data were then used to create predictive models distinguishing baseline driving from lane changes, as well as develop design guidelines for use in CAS design.

To achieve these objectives, relevant data must be based upon normal driving behavior. Until the recent data collection effort was completed, previous efforts had been constrained by the need to collect data via test tracks, over short durations, using obtrusive data collection equipment, while an observer was present (these limitations are discussed in detail at the end of this chapter). Now, for the first time, a large database of driving maneuvers has been assembled. This database is based on a field experiment in which lane change data were collected.

CHAPTER 2: LITERATURE REVIEW

This chapter describes much of the relevant work that has been conducted on lane changes and lane-change behavior, and it identifies numerous research needs for this topic area. Although the literature review is comprehensive in identifying these needs, not all of the identified research needs were addressed by this dissertation. Several subsections on lane changing include definition of a lane change, crash scenarios, monitoring surrounding zones, crash avoidance systems, relevant parameters, the lane change sequence, field observation, and a summary of needed data.

Definition of a Lane Change

A lane change has been defined as a deliberate and substantial shift in the lateral position of a vehicle (Chovan et al., 1994). Worrall and Bullen (1970) described a lane change in three parts. First, the head portion is the time and distance required for a vehicle to move from a straight-ahead path to the first intercept of the lane line. The actual lane change is begun when a vehicle first encroaches on the lane line between the original and destination lane. Secondly, the maneuver is ended once the vehicle has completely crossed that line. Finally, the tail portion of the maneuver is the time and distance required for a vehicle to return to a straight-ahead path in the destination lane after crossing the lane line.

Another view, offered by Van Winsum et al. (1999), described three sequential phases of the lane change maneuver based on steering. The first phase is an initial turn of the steering wheel to a maximum angle. The second phase begins when the steering wheel is turned in the opposite direction and ends when the vehicle heading approaches a maximum that occurs when the steering wheel angle passes through zero (straight-ahead). During the third phase, the steering wheel is turned to a maximum angle in the opposite direction to stabilize the vehicle in the new lane.

Wierwille (1984) described a lane change in two parts. A heading deviation is introduced by a steering input that results in buildup of lateral deviation. As the vehicle approaches the correct lateral position in the adjacent lane, the heading deviation is removed by applying a steering correction in the direction opposite that of the initial steering input.

For this dissertation, the start and end points of a lane change were operationally defined in terms of first lateral movement (start) and settling point (end) in the new lane. These definitions are described in detail in Chapter 3 (Method).

Lane changes can occur for a variety of reasons, such as entering, preparing to exit or exiting the roadway, in anticipation of vehicles merging onto the roadway ahead, or due to a change in the number of lanes available. Another type of lane change is a maneuver in which drivers change lanes to pass a slower vehicle ahead to maintain their current speed (Fancher, 1999; Hetrick, 1997). In fact, of all lane changes that take place on highways or freeways, a large portion include maneuvers to pass a slower lead vehicle (Eberhard et al., 1994). The “slow lead vehicle lane change” is the focus of this dissertation. This type refers to a lane change made, in which a vehicle ahead is moving at a speed slower than the subject vehicle (SV) making the lane change. The maneuver begins with the first lateral movement toward the lane line and ends when the vehicle has settled in the destination lane.

Crash Scenarios

There are two primary types of lane change crashes in which a principal other vehicle (POV) is approaching from behind the SV in the adjacent lane. In the fast approach case, there is a longitudinal gap between the vehicles prior to the start of the lane change, and this gap is closed at a substantial velocity differential (Chovan et al., 1994). This crash case is potentially dangerous and severe due to the high velocity differential (e.g., between 15 to 30 miles per hour [mph]) (Young et al., 1995). This crash case occurs infrequently.

The most frequently occurring lane change crash scenario is the proximity case. In this case, there is little or no longitudinal gap and the velocity differential between vehicles is small (Chovan et al., 1994; Wang & Knipling, 1994). Young et al. (1995) found that 78% of lane change collisions involve low closing speeds (i.e., relative speed < 15 mph). However, because of the low relative speeds that prevail, it is likely that there would be adequate time to prevent many of these collisions by warning the driver beforehand via in-vehicle alerts (Eberhard et al., 1994).

Najm and Smith (2002) have identified nine lane change *pre-crash scenarios* (with parenthesis indicating percentage of prevalence). They are: encroaching from adjacent lane (34.9%), turning (13.9%), drifting (7.7%), both vehicles attempting (avoidance) maneuvers in an encroachment situation (7.6%), passing (4.0%), avoiding a rear-end crash (3.9%), parking (3.7%), losing control (3.7%), and merging (2.5%). However, these pre-crash scenarios are predicated on the eventual outcome of a crash. When studying lane changes where no crash has occurred, it is not possible to categorize to this level of detail. The work of Najm and Smith (2002) does, however, identify that vehicles encroaching from the adjacent lane (blind spot) is the most prevalent scenario. Therefore, the separation of lane changes into fast approach and proximity cases appears to be the most relevant distinction for this dissertation, with further categorization possible for lane change maneuver types.

Monitoring Surrounding Areas

Because of the need to continually monitor areas around the vehicle, changing lanes requires high attentional and visual demand compared to normal highway or freeway driving (Shinar, 1978). These increased demands make lane changing one of the riskiest driving maneuvers (Jula, Kosmatopoulos, & Ioannou, 1999). Drivers must straddle traffic flows and are exposed to two streams of vehicles; they must also make rapid gap judgments, monitor vehicles approaching from behind and in the blind spot, and they potentially disrupt the flow of following vehicles (Redelmeier & Tibshirani, 2000). Drivers also divert attention from any developing situations farther ahead.

Forward Area

The forward area is the area in front of the SV in the same lane in which another vehicle is traveling. This area is also referred to as *headway*, defined in terms of time headway or distance (Rockwell, 1972; Van Winsum & Heino, 1996). Time headway is defined as the elapsed time between the lead vehicle passing a point on the roadway and the following vehicle passing the same point; it is calculated as the range between the two vehicles divided by the speed of the following vehicle (McLaughlin, 1998). For example, the headway would be one second for a vehicle moving at 100 feet/second at a range of 100 feet (100 feet ÷ 100 feet/second). Time headway can be thought of as a margin of safety. One rule of convention has been that headway

should be at least two seconds (Evans, 1991), which is referred to as the “two-second rule.” This is often taught in driver’s education classes. Another rule is the National Research Council rule of “one car length for every 10 mph,” which few drivers follow (Rockwell, 1972).

Four distinct headway zones have been recognized (Ohta, 1993). The *danger zone* is within 0.6 s of the vehicle ahead. Within this zone, the driver usually experiences a feeling of danger of a collision with the vehicle ahead. The *critical zone* is associated with the range between 0.6 s and 1.1 s. This is the zone between the danger zone and the minimum subjective safe distance border. A driver within this zone should decelerate to get beyond the critical zone. The *normal driving zone* is associated with the range between 1.1 s and 1.7 s--the minimum subjective safe distance (1.1 s) and the distance that drivers feel is not too far or near to the vehicle ahead (1.7 s). Drivers typically stay within this normal zone. Many drivers feel obligated to drive within this zone, perhaps due to social traffic pressure, although it has been shown to be closer than they would prefer (Ohta, 1993). Others stay within this zone as a means of preventing other drivers from cutting into their lane (Fancher et al., 1998; Ferrari, Cascetta, Nuzzolo, Treglia & Olivotto, 1984; Saad, 1997). The *pursuit zone* is beyond the normal driving zone and has a headway of > 1.7 s. Many drivers are uncomfortable here because this zone may be outside the social norm (Ohta, 1993). That is, drivers may tend to stay in the pursuit zone because maintaining a headway > 1.7 s may feel “too far” for most drivers.

Under normal circumstances, it appears that drivers travel with headways between 0.5 s and 4 s, and, in general, drivers attempt to maintain a minimum of 2.0 s, according to Rockwell (1972). The average appears to be 1.22 to 1.52 s (Table 2.1). Van Winsum and Heino (1996) reported the mean headway of 1.52 s for 54 drivers traveling at 70 km/h in a driving simulator in a vehicle-following task. Allen, Magdaleno, Serafin, Eckert, and Sieja (1997) reported the mean headway of 1.22 s, with values ranging between 0.58 s and 1.90 s, in a highway experiment involving 36 drivers. Some participants spent a significant portion of their vehicle-following exposure with headway < 1.0 s, which might be considered fairly risky behavior (Allen et al., 1997; Saad, 1997). Results from a recent field operation test indicate that the most likely value for headway was 0.8 s for speeds > 55 mph (Fancher et al., 1998). Test vehicles were given to 108 volunteer drivers to use as their personal vehicles for two or five weeks. For slow lead-vehicle lane changes, some drivers allow a short headway prior to a lane change, perhaps as short as 0.5 s (50 feet at a speed of 100 ft/s) (Rockwell, 1972; Saad, 1997).

Recently, Fancher (1999) reported results from a field operation test of manual and automatic cruise control (ACC) driving. For a total of 2,607 manual lane changes in which a preceding vehicle was present, the average time headway was reported as 1.6 s, as illustrated by Figure 2.1. Note that this figure is a replication based upon the original report--values above 3 s were ignored and the range of values is large. In addition, the ordinate was percentage observation, such that the sum of the observations (as binned) was equal to 100%. Thus, the very last point plotted in Figure 2.1 shows that only 2% of all observations occurred at 3 s. However, the bounds set on the graph (0.1 to 3 s) may have been somewhat arbitrarily selected (J.R. Sayer, personal communication, September 4, 2002).

Table 2.1: Average Time Headway from Three Relevant Studies.

SOURCE	M	SD	N
Van Winsum and Heino (1996)	1.52 s	0.27	54
Allen, Magdaleno, Serafin, Eckert, and Sieja (1997)	1.22 s	0.38	36
Fancher (1999)	1.60 s	0.80	108

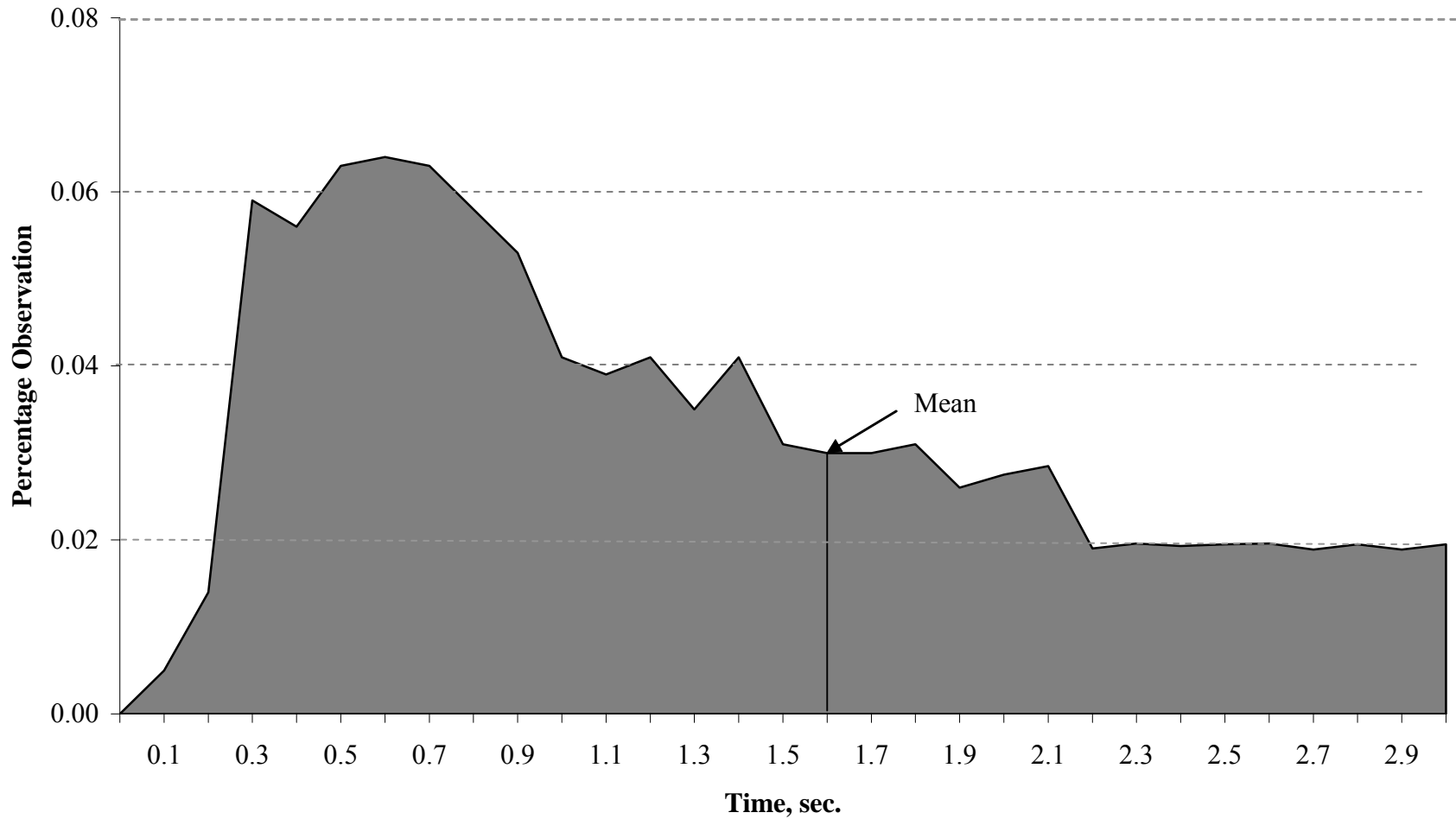


Figure 2.1. Headway Time for Manual Lane Changes with a Preceding Vehicle (Replicated in part from Fancher, 1999).

Forward Adjacent Lane Area

The forward area in the destination lane is another subject of concern. The available distance is very likely to influence the decision to change lanes. Jula et al. (1999) analyzed the kinematics of the vehicles involved in lane changing and studied the conditions under which crashes can be avoided. This approach is promising, in that the minimum longitudinal spacing requirements can be calculated in preparation for a lane change for purposes of crash avoidance. However, they did not identify any sources for headway data, as the focus of the paper was to explain how traffic simulation could be used to calculate minimum longitudinal spacing.

Rearward Adjacent Lane Area

Some drivers are willing to change lanes even when a vehicle is approaching from behind in the adjacent lane. This scenario is more likely to lead to a crash as the driver attempts to change lanes and strikes, or is struck by, a vehicle in the adjacent lane (Chovan et al., 1994). The rearward area is divided into rear zones related to the lane change crash scenarios previously described (i.e., proximity and fast approach). The zones include the *proximity zone* (PZ) and the *fast approach zone* (FAZ) (Talmadge et al., 2000). The PZ is the area in the adjacent lane from four feet in front of the front bumper of the SV to 30 feet behind the rear bumper of the SV. This area generally includes the blind spots and the immediate areas beside and behind the SV. The most common lane change crashes appear to be those occurring in the PZ (Chovan et al., 1994). The FAZ is the area in the adjacent lane from 30 to 162 feet behind the rear bumper of the SV. At 100 ft/s (68.2 mph), a vehicle within this zone would have between 0.3 s to 1.6 s of time headway. Both the PZ and the FAZ refer to areas that should be monitored before lane change initiation; however, there are few data regarding the PZ and FAZ. Figure 2.2 illustrates the PZ and the FAZ.

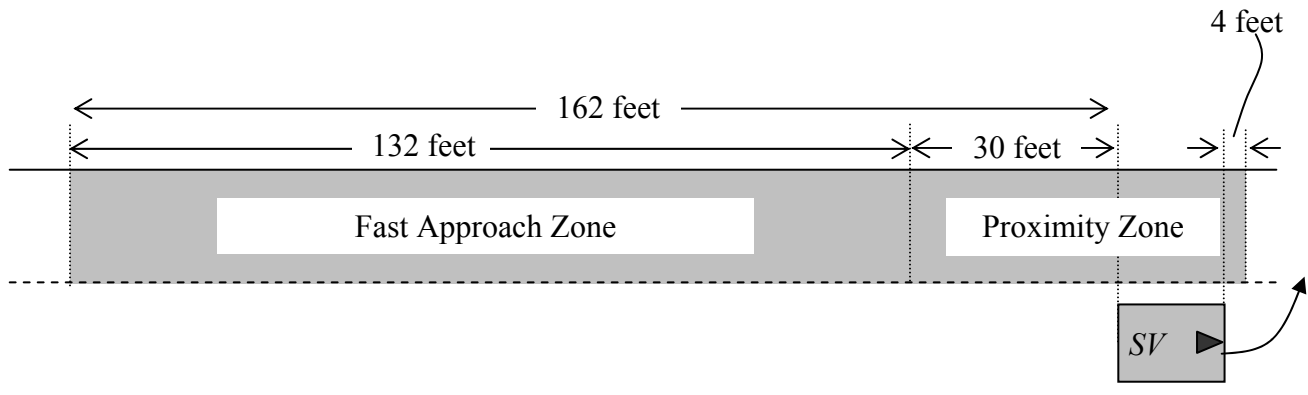


Figure 2.2. Fast Approach Zone and Proximity Zone in Relation to Subject Vehicle.

Crash Avoidance Systems

Crash avoidance systems (CAS) have been proposed to reduce lane change crashes by alerting/warning drivers of the presence of a vehicle in the PZ or FAZ (Eberhard et al., 1994; Talmadge, et al., 1997). A CAS is an in-vehicle, integrated system of sensors (e.g., radar, laser, or optical), used to detect hazards and displays (e.g., visual, audio, haptic) and to issue alerts or warnings when a potentially dangerous situation is present. A lane change CAS (LCAS) would

enhance the ability of the driver to perform safely by monitoring surrounding areas and providing information to the driver about vehicles approaching from the rear in the desired adjacent lane. The driver would then respond to the LCAS alert and would be more able to react appropriately when preparing to make a lane change.

A CAS should assist the driver in maintaining awareness of surrounding vehicles. However, an understanding of driver behavior under normal conditions prior to lane change initiation is essential for the design of a safe and usable CAS. A CAS should detect what the driver does not detect and provide timely information allowing the driver to drive more safely; however, this information must not be a distraction to the driver (Chovan et al., 1994; Eberhard, Moffa, Young & Allen, 1995). Understanding driver behavior will assist designers in the placement, format, and timing of in-vehicle warnings so that a CAS will fit well with drivers' behaviors and expectations. A LCAS can then be successfully designed, implemented, and deployed, and it can be smoothly integrated into the driving environment.

Relevant Parameters

This literature review continues with a discussion of the various data or relevant parameters that are needed for CAS development and operation. Relevant parameters include velocity, frequency, duration, acceleration, range, range-rate (velocity differential), time-to-collision (TTC), vehicle position, turn signal use, and eye movements.

Velocity

For a CAS to be effective, the underlying warning/advisory algorithm must be sound. This algorithm requires both SV and POV velocity data, along with several other parameters. The absolute velocity of the SV (the vehicle with the CAS) must be known. Range-rate data can be acquired via radar equipment that monitors vehicles ahead of and behind the SV. The absolute velocity of surrounding vehicles can then be derived using these data. Finally, velocity data can be used in conjunction with appropriate algorithms to calculate details relevant to adjacent vehicles (e.g., velocity, range, position, range-rate, and TTC), to advise or alert the driver when it is unsafe to change lanes (Eberhard et al., 1995; NHTSA, 1996; Young et al., 1995), or when a collision is imminent (Campbell, Carney, & Kantowitz, 1998).

Young et al. (1995) have suggested that police accident reports could be examined to derive velocity and kinematic information for lane change *collisions*. It is unknown if this has been attempted, but police reports are often not that complete regarding other vehicles. Bascuñana (1995) has examined the dynamic conditions that set apart safe lane changes from unsafe lane changes. He quantified four cases of lane changes in terms of the relative distances and velocities between vehicles at lane change initiation. The safety of the maneuver was described as a function of braking time, acceleration, separation, and velocity. However, the author concluded that the capabilities of potential countermeasure systems need to be verified based upon results of test track experimentation.

Distributions of the relative speeds in two-vehicle crashes are not readily available (Eberhard et al., 1994). However, the velocity differential between vehicles is probably between 5 and 15 mph for the proximity crash case (Chovan et al., 1994; Wang & Knippling, 1994; Young et al., 1995). For the fast-approach crash case, the velocity differential is typically 15 to 30 mph; Young et al. say that 94% of fast-approach crashes have relative speeds that are less than 30 mph. Subject vehicle (SV) speed distributions and the closing speed distributions are different for lane changes to the right and to the left, according to Eberhard et al. (1995). This is probably

due to the tradition of slower vehicles keeping to the right lanes and faster vehicles keeping to the left lanes. That is, the speed of a slow lead vehicle would likely influence the speed (and position) of a vehicle behind it (Eberhard et al., 1994). Hetrick (1997) and Fancher (1999) reported that drivers are likely to change lanes to pass slow lead vehicles and maintain their current speed.

Frequency

Vehicle velocity may be correlated with lane change frequency. For example, drivers who maintain a high average velocity relative to traffic may display more lane changes (i.e., weaving in and out of traffic) than drivers who maintain lower velocities. Ferrari et al. (1984) suggested that differences exist according to a driver's speed and lane choice. A relatively fast driver may choose the left (faster) lanes, where there is a low likelihood of being approached by another vehicle from behind and also of coming upon a slow lead vehicle. This same driver in the slow (right) lane would need to perform frequent lane changes due to slow vehicles ahead. Likewise, a relatively slow driver may choose to drive in the right lane, given that there is a lower probability of needing to pass slower vehicles (e.g., based on low traffic density). This same driver, if in the left lane, would likely be compelled to change lanes frequently due to faster moving vehicles to the rear. The frequency of lane changes due to a slow vehicle ahead is has not been determined.

Duration

Lane change duration for high velocity drivers might be shorter, as compared to low velocity drivers; however, not many on-road duration data exist. Lane change times from 2.0 s to 16.0 s are taken as the initial range within which to examine lane change CAS warning requirements (Chovan et al., 1994). Lane change duration has been investigated by using an aerial photography technique to make estimates of lane change duration (Worrall & Bullen, 1970). The maneuver was split into head (first lateral movement to lane line intercept) and tail (line intercept to straight-ahead movement) portions. The average head maneuver was 1.25 s ($SD = 0.4$) and average tail time was 1.95 s ($SD = 0.5$). Therefore, the average lane change duration was approximately 2.3 s to 4.1 s. However, it is believed that the total lane change times were underestimated because of resolution and model-prediction limitations (Chovan et al., 1994). It is unclear why the duration was so low; perhaps the body of the lane change was not included in their totals.

In a literature review on lane changes, Finnegan and Green (1990) reported that lane changes take between 4.9 s and 7.6 s (including visual search time). Tijerina et al. (1997) described a pilot study of both highway and city street driving. For the city streets, lane change duration was between 3.5 s and 6.5 s, with a mean of 5.0 s. For the highway, the range was 3.5 s to 8.5 s, with a mean of 5.8 s. In a study by Hetrick (1997), the distribution of lane change times ranged from 3.4 s to 13.6 s, with a mode of 6.0 s for 282 lane changes. In this study, 16 participants drove on city and highway segments in an instrumented vehicle for 1.5 hours, and an observer was present. A recent study investigated the influence of fatigue on local short-haul truck drivers (Hanowski, Wierwille, Garness, & Dingus, 2000a). The majority of lane changes were made on local urban and suburban streets and roadways at relatively low speeds (e.g., < 45 mph). They concluded that drivers who were fatigued spent more time looking at the center-forward direction and made significantly shorter lane changes ($M = 3.73$ s) as compared to lane changes completed by non-fatigued drivers ($M = 4.79$ s). The average lane change duration was

4.52 s for 260 normative lane change events. The range of duration values was 1.1 to 16.5 s ($SD = 1.71$) for normative events (R. J. Hanowski, personal communication, June 20, 2002). Lane changes started when the wheel of the vehicle crossed the lane line and ended when the vehicle settled in the new lane, and it did not include the head duration. However, if the average lane change duration of 4.79 s is added to the Worrall and Bullen (1970) value of 1.25 (the head), the total lane change duration would be 6.04 s, a value that falls within the range of previous findings (Chovan et al., 1994; Finnegan & Green, 1990; Hetrick, 1997; Tijerina et al., 1997). Table 2.2 summarizes these findings. Additional data are needed on normal lane change times and their distribution (Chovan et al., 1994), as no extensive sources of normal lane change time data currently exist.

Table 2.2: Lane Change Duration as Reported by Various Sources.

SOURCE	Range	Mean/Median/Mode	Notes
Worrall & Bullen (1970)	2.3 s to 4.1 s	Median = 3.2 s	Underestimated due to resolution
Finnegan & Green (1990)	4.9 s to 7.6 s	Median = 6.3 s	Including visual search time
Chovan et al. (1994)	2.0 s to 16 s	-	Initial range for CAS
Tijerina et al. (1997)	3.5 s to 6.5 s	Mean = 5.0 s	City streets
Tijerina et al. (1997)	3.5 s to 8.5 s	Mean = 5.8 s	Highway
Hetrick (1997)	3.4 s to 13.6 s	Mode = 6.0 s	City and highway segments
Hanowski et al. (2000a)	1.1 s to 16.5 s ($SD = 1.71$)	Mean = 4.8 s (6.0 s if head of 1.25 is added)	Local short-haul truck drivers, speeds < 45 mph; does not include head

Acceleration

Driver acceleration patterns while changing lanes also need to be addressed and should be investigated. It would be helpful to know if drivers accelerate while changing lanes or if constant longitudinal velocity is maintained (Chovan et al., 1994). It is likely that acceleration rates would be different for straight-ahead driving as compared to the period leading up to a lane change in which a slow vehicle is ahead. Typical acceleration rates for straight-ahead driving at freeway speeds (e.g., 60 mph) are estimated to be 1.5 ft/s² (0.5 m/s²) for sedans and 1.3 ft/s² (0.4 m/s²) for SUVs, based on vehicle dynamics models reported by Rakha, Snare, and Dion (2003) and Snare (2002). Information about acceleration during lane change latency might be useful. For example, upon encountering a slow lead vehicle, it can be assumed that the SV may decelerate (a negative acceleration) to maintain a reasonable gap until the driver determines it is safe to change lanes. If data on typical acceleration rates could be collected, these data might be used for discriminating between straight ahead and lane changing behavior for warning systems; however, no acceleration data are currently available for pre-lane change periods.

After the lane change is completed, it is possible that drivers accelerate to pass a slow vehicle when conditions are perceived to be more difficult than normal (e.g., to pass a large truck) (Shinar, 1978). Note that, although acceleration patterns have been identified by some researchers as a research need, acceleration was not investigated as part of the current effort.

Steering

Steering wheel movements might be important to distinguish between lane changing and straight-ahead driving. Preparatory steering movement away from the direction of lane change could possibly be used as an indicator of the driver's intent to change lanes (Chovan et al., 1994; Moffa et al., 1996).

Range

Range is defined as the distance from the front bumper of the following vehicle to the rear bumper of the lead vehicle. This is the distance from the SV to the slow lead vehicle (POV) in the same lane. In the case of a vehicle approaching from behind the SV, range is the distance from the front bumper of the adjacent rear vehicle (POV) to the rear bumper of the SV, along a longitudinal axis through either of the vehicles. Range in relation to the SV and surrounding vehicles is illustrated in Figure 2.3. The range to the slow lead vehicle is of concern when making a lane change. The range to the vehicle ahead should be monitored constantly while driving, especially when preparing for a lane change.

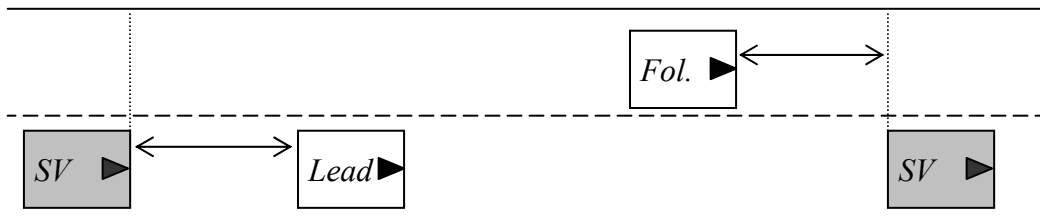


Figure 2.3. Range from SV to Lead POV and from Following POV to SV.

In a recent field operation test of manual and ACC driving (Fancher, 1999), the average range was 153.3 feet ($SD = 103.6$ feet), with 27% of lane changes occurring within 70 feet of the preceding vehicle, for a total of 2,607 manual lane changes. Figure 2.4 illustrates the distribution of range reported. Note that the range of values is quite large. The ordinate was a percentage observation, such that the sum of the observations (as binned) will equal 100%. The very last point plotted in Figure 2.4 shows that only 1% of all observations occurred at 405 feet. Note that the bounds set on that graph (15 to 405 feet) may have been somewhat arbitrarily selected (J.R. Sayer, personal communication, September 4, 2002).

Range-Rate (or velocity differential)

Range-rate (or velocity differential) is the rate at which the range between two vehicles is changing. It is measured in terms of relative velocity, in which the velocity of one vehicle is subtracted from the velocity of the other vehicle. Range-rate is of concern in terms of distance from the SV to a nearby vehicle (i.e., in adjacent lane). Range-rate is reported in either miles per hour (mph) or feet per second (ft/s).

Reilly, Pfefer, Michaels, Polus, and Schoen (1989) reported that drivers enter the roadway with a 9 mph velocity differential. This conclusion was based on data of vehicles entering the roadway on speed-change lanes in which the SV was pulling in front of another vehicle already on the freeway. However, this study considered only those vehicles merging into

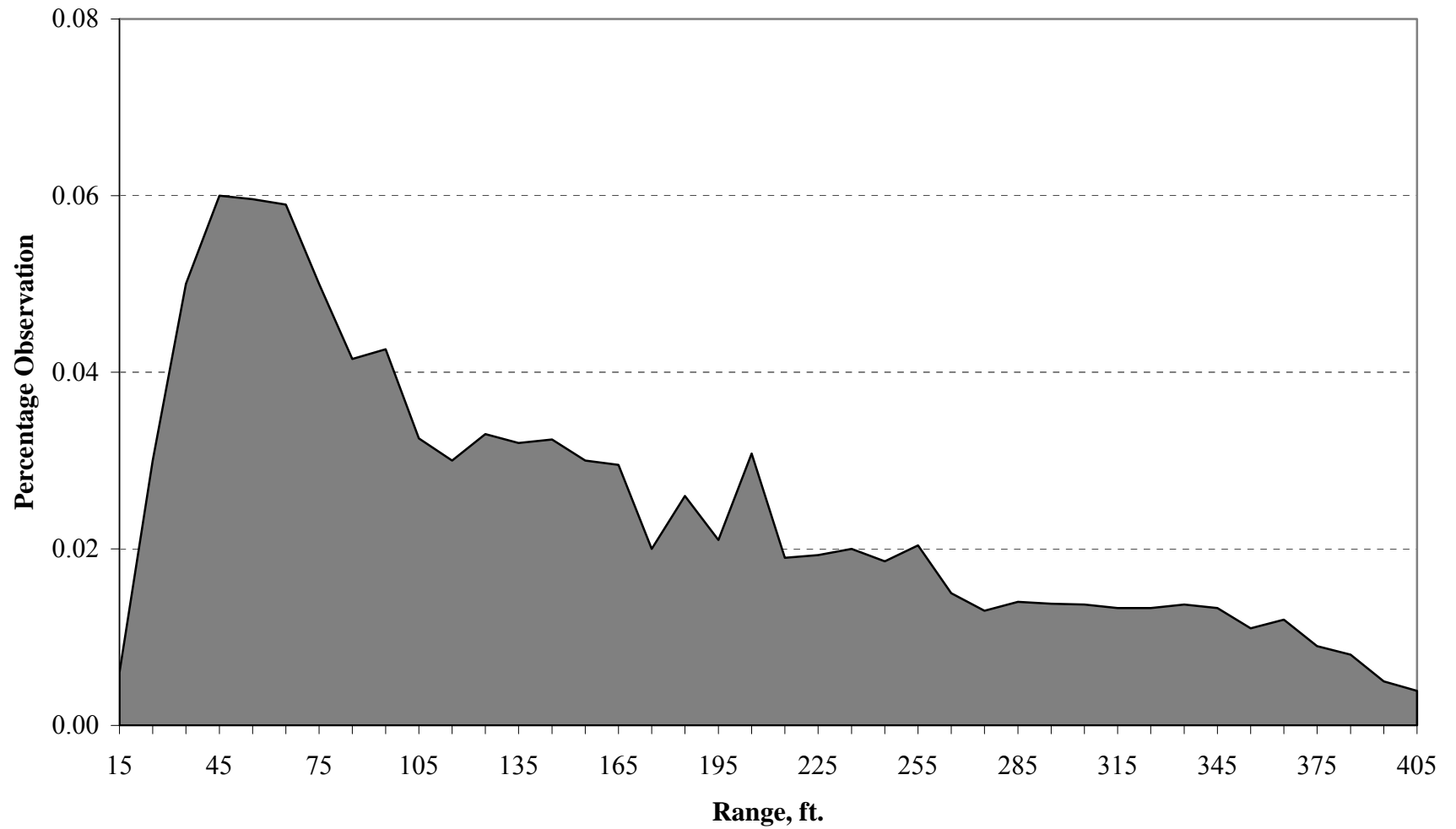


Figure 2.4. Range for Manual Lane Changes with a Preceding Vehicle (Replicated in part from Fancher, 1999).

relatively small freeway gaps during periods of moderate to high traffic volumes, so this velocity differential might be considered extreme for lane changing.

Staplin et al. (1998) reported that, for speed differentials of 5 mph, younger participants (18-45 years old) estimate that a much smaller distance is required (95 feet) as a minimum safe gap for a vehicle overtaking. In comparison, older participants (> 65 years old) estimated a required distance of 242 feet. For speed differentials of 10 mph, younger participants estimate that a much smaller distance is required (128 feet) as a minimum safe gap, as opposed to older participants (261 feet). Overall, to make a lane change with a 10 mph differential speed, only two-thirds of the members of the younger group were willing to make the lane change at a 200-foot vehicle separation, where a lane change remains just feasible under normal operating conditions. Only one-third of this group would make the maneuver with a 25 mph speed differential. For the case in which the speed differential is 25 mph and a vehicle is only 100 feet away, a lane change that is (successfully) made can only be interpreted as a serious driving error. More recently, in a field operation test of ACC, the average range-rate was reported to be -4.1 feet/second ($SD = 10.0$ ft/s), as illustrated by Figure 2.5 (Fancher, 1999).

What is needed is information about how normal lane change time is affected by the velocity of vehicles involved. Collecting and analyzing velocity differential data may be useful for understanding the effect that an approaching vehicle has on gap acceptance of drivers (i.e., when they choose to change lanes in relation to surrounding vehicles). Situations in which technology could best aid the driver could then be identified using these data (Knipling, 1993). Having access to the distribution data of lane changes and relative speeds of passing vehicles would be extremely valuable (Chovan et al., 1994; Eberhard et al., 1994).

Time-to-Collision

Time-to-collision (TTC) is the time required for two vehicles to collide if they continue on their present speed and path (Van Winsum & Heino, 1996). The TTC is calculated as the range between the two vehicles divided by their range-rate or relative velocity (ΔV). Take the case of two vehicles that are 100 feet apart. If the front vehicle is moving at 100 feet/second and the following vehicle is moving at 120 feet/second, the range-rate would be 100 feet/second minus 120 feet/second, or -20 feet/second. To calculate the TTC, 100 feet is divided by -20 feet/second. Therefore, the TTC is 5.0 s. In other words, it would take 5.0 s for the following vehicle to collide with the lead vehicle if velocity was constant. However, the TTC parameter assumes constant speed and does not account for vehicle acceleration (Smith, Najm, & Glassco, 2002). Regardless, Talmadge et al. (1997) concluded that TTC is a likely candidate for use in CAS to activate warnings for drivers. They used an experimental CAS built by the Vehicle Research and Test Center (VRTC) of East Liberty, Ohio, for a NHTSA effort, using a TTC collision algorithm. The CAS activates the driver warning system based on this algorithm. Results suggest that a conservative amount of warning time would be 3.0 s for most drivers.

Turn Signal Use

Another important factor for lane changing is the use of the turn signal; however, data are limited on turn signal use. In a study in which an experimenter in the passenger seat gave directions to the driver, Hetrick (1997) found that 92% of lane changes were indicated by a turn signal. In a small-scale pilot study, Tijerina et al. (1996) reported that drivers did not use their turn signal for 14.6% of lane changes on highways (10.3% for city streets). However, it is likely

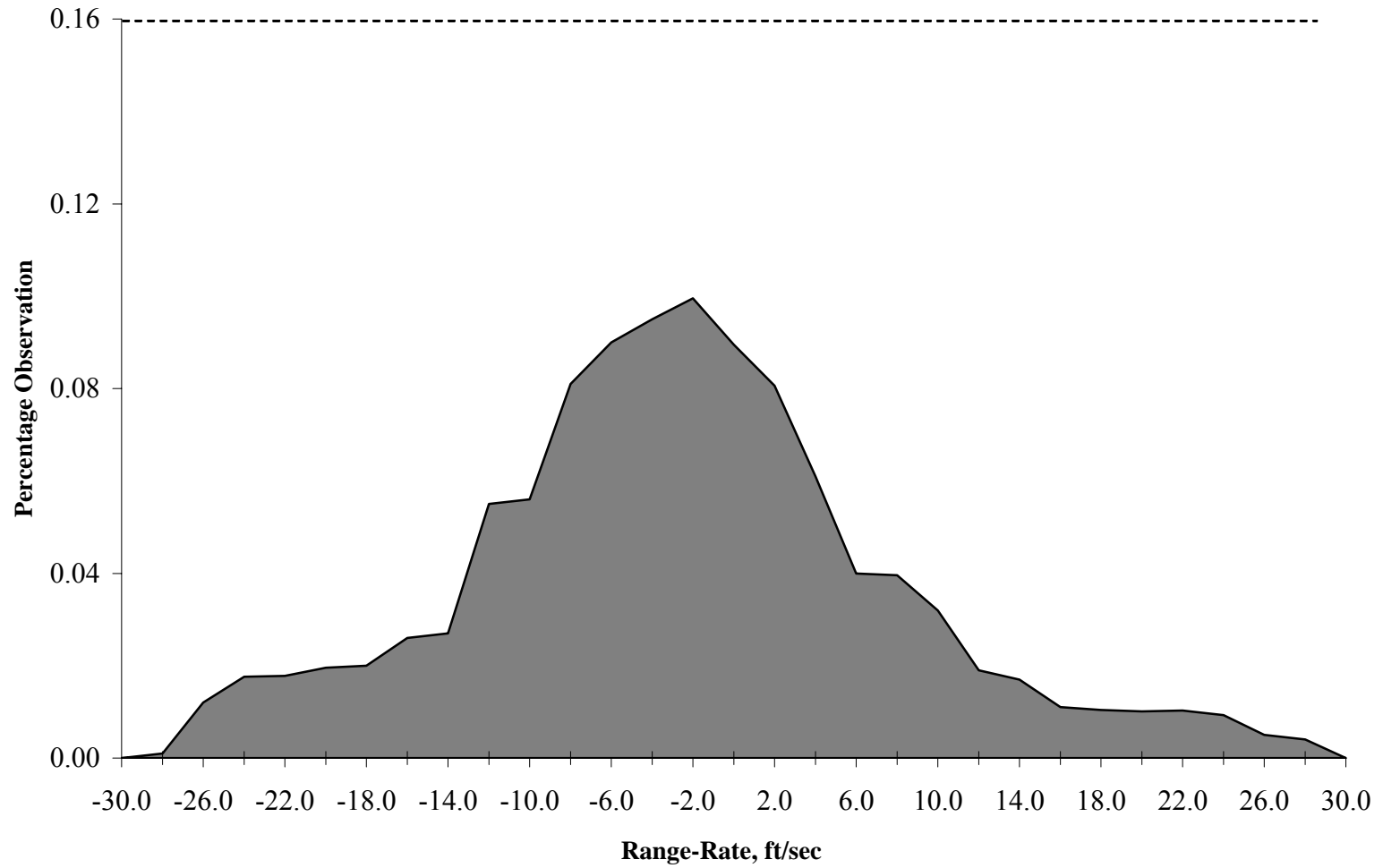


Figure 2.5. Range Rate for Manual Lane Changes with a Preceding Vehicle (Replicated in part from Fancher, 1999).

that experimenter presence in these studies influenced turn signal compliance. The distribution of turn-signal onset time ranged from -2.42 to 3.62 seconds (with 0 indicating lane-change start) (Hetrick, 1997). In other words, the manner in which turn signals are used may vary greatly among drivers, with some drivers activating the turn signal after beginning the lane change maneuver. The use of data from actual traffic is recommended (Hetrick, 1997), and this data should specifically regard the speed of lane changes by non-signaling vehicles and the distribution of lateral separation between vehicles on various types of roads. However, at this point, timing and turn signal use is unknown for lane changing during actual driving in which an experimenter is not present.

Turn signal use is an important factor relative to CAS implementation. There are two likely implementations of a lane change CAS. In one such scenario, the CAS is activated by the turn signal (or some other indication of lane change initiation). In the other scenario, the CAS is always on when the vehicle is moving forward (Moffa, Austin, Dow, Ikizyan, & Hibben 1996). There is, however, an apparent split in opinion of how turn signal use should relate to CAS warnings. According to Hyland (1995), there is a 50/50 split between drivers who want the warning system activated only with the turn signal and those who want it in monitor mode at all times. According to Eberhard et al. (1995), participants driving a simulator responded in favor of turn signal activation of CAS warnings. The level of warning issued may be tied into turn signal use; according to Mazzae and Garrott (1995), auditory warnings should only be provided when the turn signal is activated (at least for side collision avoidance systems). Evaluating data on turn signal use in relation to lane changing will likely be helpful when addressing these issues.

Eye Movements

Driving is "guided chiefly by vision," (Gibson & Crooks, 1938, p. 454) where information is continuously monitored and gathered (Hills, 1980; Mourant & Rockwell, 1970; Wierwille, 1984; 1993). Since Gibson and Crooks's statement, perhaps the first investigation relevant to eye movement was that of the eye vantage point performed by James Meldrum of Ford. Meldrum conducted an eye position survey to identify position contours (Henderson, 1985). Termed an "eyellipse," this allowed automobile designers the ability to assess what and where the driver can see (e.g., view out the windshield, view of instrument panel).

In contrast to *what* drivers can see is the research related to *where* drivers are actually looking while they are driving. Measures of eye movements have been investigated in terms of the number of eye glances, total glance time, mean glance time to a particular location, total eyes-off-road time, and total task time (i.e., the time to complete a task). For example, driving research has been conducted on the performance of completing in-car tasks such as adjusting the radio, viewing in-car displays (e.g., speedometer), or interacting with a navigation system (Dingus, Antin, Hulse, & Wierwille, 1988; Gellatly & Kleiss, 2000; Kurokawa & Wierwille, 1990; Tijerina, Palmer, & Goodman, 1999). Visual glance duration and the number of glances per task were investigated while performing conventional in-vehicle tasks and navigation tasks (Wierwille, Antin, Dingus, & Hulse, 1988). Findings indicated that glance frequency varied depending upon the task and that glance duration for a single glance ranged from 0.62 s to 1.63 s. The mean number of glances across all tasks was between 1.26 and 6.52 glances. Zwahlen, Adams, and DeBald (1988) reported that "out of view" glance times (e.g., rear view mirror, speedometer) ranged from 0.5 s to 2.0 s during straight driving. Findings from several additional eye movement studies relevant to lane changing are reviewed in the next sub-sections.

Mirror Glances

An early study by Robinson et al. (1972) involved measuring head movements to study the visual search of drivers while changing lanes on a highway. (The relationship of head movement to eye movement was also investigated and was found to be stable.) Visual search patterns were recorded, including movements back (blind spot), to the side, and to the mirrors. Results indicated that lane changes to the left had more searches than lane changes to the right. This finding was supported by Taoka (1990), who reported that drivers use the rear view and left-side mirror much more than the right-side mirror. In a study of the average duration of glances to rear view and side mirrors, drivers relied more on the rear view mirror than on the right mirror for lane changes to the right (Mourant & Donohue, 1977). Robinson et al. (1972) reported that both the left mirror and blind spot were checked during left lane changes, and the rear view mirror and blind spot was checked for right lane changes. It appears that head turns to check the blind spot were only observed in conjunction with lane changes. While traveling straight ahead, only glances to the mirrors were made and drivers did not make head turns to the side or rear of the car (Mourant & Donohue, 1977). These findings may be useful to CAS designers, especially if confirmed based on the analyses of the data collected from this field experiment. For both right and left lane changes, the rear view mirror is used often. In the future, CAS might use head-turn information to sense when a lane change is about to begin, assuming head-turns could be successfully monitored.

Mirror Glance Duration

Based on available literature discussed in this section, mirror glance times range from 0.8 s to 1.6 s ($M = 1.1$ s). Searches to the rear (blind spot) appeared to require a minimum value of 0.8 s. Nagata and Kuriyama (1985) investigated the influence of driver glance behavior in obtaining information through door and fender mirror systems. For door mirror systems, they reported that the average glance duration to the near-side (i.e., right side in this case) mirror was 0.69 s. However, some portion of the duration may be attributable to longer transition time due to angle differences from the vertical axis (42 degrees for near-side). Rockwell (1988) reported that the average glance duration to the left mirror was 1.10 s ($SD = 0.33$ s). This finding was consistent among different participants in three different experiments that took place over a six-year period and used the same data gathering and reduction technique. Taoka (1990) modeled eye glance distributions of Rockwell and found that they could be well represented by means of a lognormal distribution. Taoka reported that the average time for viewing the left-side mirror was also 1.10s ($SD = 0.3$ s). The 5th percentile value was 0.68 s and the 95th percentile was 1.65 s. For right-side mirror glances, Nagata and Kuriyama (1985) reported that average glance duration for the far-side mirror was 1.38 s (angle difference from the vertical axis of 70 degrees), while Rockwell reported an average glance duration of 1.21 s (10% larger than left glances), with an approximate standard deviation of 0.36 s. For the rear view mirror, Taoka (1990) reported that the average glance time was 0.75 s ($SD = 0.36$ s). The 5th percentile value was 0.32 s and the 95th percentile was 1.43 s.

Mourant and Donohue (1974) examined the total glance time for lane changes. The number of glances and the duration of each glance during lane changes was recorded as participants drove on a freeway and an experimenter monitored the driver from the back seat. Results indicated that the average time for a novice driver to complete the visual sampling for a left lane change was 2.4 s, consisting of 1.38 glances to the left-side mirror, 0.76 glances to the inside (rear view) mirror, and a head turn. Data were also obtained for experienced and mature

drivers, and similar patterns of glancing were observed. Obtaining data in terms of glance duration and timing of eye movements for a variety of drivers may be useful in understanding lane change latency. For example, knowing the duration of glances and glance location during lane change latency could be useful for the timing of CAS displays and their design. In addition, characterizing the search and scan patterns of drivers during latency may be important for CAS developers.

Search and Scan Patterns

Early research included the investigation of visual search and scan patterns while driving (Mourant, Rockwell, & Rackoff, 1969; Mourant & Rockwell, 1970; 1972). It was found that drivers spent more time looking ahead as they became familiar with a route, they confined their sampling to a smaller area ahead, and they were better able to detect potential traffic threats (e.g., movement in the periphery). Mourant and Rockwell (1970) found that peripheral vision was used to monitor other vehicles and lane line markers, novice and experienced drivers differed in their visual acquisition process, and novice drivers may be considered to drive less safely.

In another study, it was found that specific eye glance patterns take place before lane change initiation (Tijerina et al., 1997). Based on the results collected during road studies, the researchers used a Markovian process to examine the probability of movement from one location to another. Link diagrams showing glance location and the associated probabilities of a glance to that location during the 10.0 s prior to the lane change start were then created. For a sedan lane change from right to left, the probability of glancing at the forward view was 0.41, the probability of glancing at the left mirror was 0.22, the probability of glancing in the rear view mirror was 0.21, and the probability of glancing over the left shoulder (blind spot) was 0.08. The probability of a glance transition between different locations was also provided (e.g., 0.37 between the forward view and the rear view mirror).

Tijerina (1999) highlighted pertinent findings from the Tijerina et al. (1997) study. The percentage of lane changes in which side and rear view mirrors were used differed for left and right lane changes. The left side mirror is used more frequently in maneuvers to the left (between 65 and 85% in the study) than is the right-side mirror for maneuvers to the right (between 36 and 52%). However, the rear view mirror is used more often for right lane changes (between 82 and 92%) than for left lane changes (between 56 and 67%). This supports the earlier finding that drivers depended most heavily on the rear view mirror for lane changes to the right (Mourant & Donahue, 1977). Tijerina et al. (1997) found that, for lane changes to the left, glances to the rear view and left mirrors had approximately the same probability (0.21 and 0.22 respectively). Shoulder glances were more frequent for left lane changes than right lane changes.

Staplin et al. (1998) evaluated mirrors in the context of a lane change task. One rationale for conducting the study was that lane changing and merging were involved in 24% of crashes related to problems of visibility from vehicles. Results from self-reports indicated that all younger participants (aged 18-45) and two-thirds of the older participants (> 65 years old) reported using the left mirror, followed by a blind spot check before lane-change initiation to the left. One-third of the older participants reported using the left mirror alone (no blind spot check) before initiation. The conclusion was that the sampling of mirrors might be limited to only a single glance in high density lane change situations, where instantaneous “go/no-go” decisions sometimes have to be made. However, these results may not be representative of normal driving, since participants were instructed to maintain a forward view until a cue was given indicating that they were to switch attention exclusively to the left mirror until responding.

A recent field study investigated the influence of fatigue on critical incidents involving local short haul truck drivers (Hanowski et al., 2000a). Fatigued drivers involved in critical incidents when making lane changes spent more time looking in irrelevant locations (i.e., locations other than out-the-windshield, out-the-windows, at the mirrors, or at the instrument panel). The mean proportion of time spent looking at irrelevant locations was 0.08. However, during normal lane changes (not a critical event), the mean proportion of time that drivers spent looking at irrelevant locations was 0.03, a significant difference. In terms of eye behavior, it appears that fatigued drivers involved in critical incidents pay less attention to relevant locations such as the road ahead and appropriate mirrors. This finding might be important for CAS designers in terms of creating different systems for passenger vehicles vs. commercial vehicles, where issues such as scanning patterns and fatigue may differ.

Recarte and Nunes (2000; 2003) recently conducted testing in highway and road traffic to investigate the consequences of performing mental tasks on visual search while driving. In these studies, they used an unobtrusive eye tracking system with an infrared video camera installed on the dashboard. Specifically, they tested whether high attentional workload produced attentional focus narrowing. When driving on highways, glances to the rear view mirror were 10 times more frequent than when driving on conventional roads (likely due to overtaking maneuvers on the highway) and glances to the left mirror were more than twice as frequent on highways as on conventional roads. During normal driving, the instrument panel was glanced at almost twice as often as the left mirror, and the left mirror was glanced at more than twice as often as the rear view mirror, depending on route. When driving normally, 14/1000 eye fixations were directed at the rear view mirror. This decreased to 4/1000 when performing a verbal task and 2/1000 for a spatial-imagery task. When performing mental tasks, glances toward the rear view mirror declined substantially and frequency of visual inspection using the left (side) mirror decreased. During ordinary driving (no task), the percentage of glances to the mirrors or instrument panel was 3 to 4% of the total number of glances observed; this decreased to 1% or less when a mental task was performed. A reduction of the visual inspection window, an imaginary box representing both the horizontal and vertical gaze of the driver, was also observed. While driving and performing mental tasks, a reduction of the window was observed in the horizontal direction between 25 to 40%. In the vertical direction, the visual inspection window was reduced by between 40 to 60%, as compared to the window observed during ordinary driving.

This research, while not specific to lane changes, has many implications. It appears that differences exist in mirror and instrument panel glances, depending on route, mental workload, fatigue level, and driving situation. The authors note some limitations, however. As the visual inspection window narrows, there may be less information available; therefore, driving may become more risky. However, this is only true if all attentional resources are focused solely on relevant driving information. When observing a reduction in the inspection of the speedometer or mirrors, or of the functional visual field, it is not known whether the eliminated glances correspond to relevant or irrelevant information, as far as road safety and strategy are concerned.

Understanding eye glance patterns may be useful in developing and evaluating potential lane change CAS. Conclusions from Tijerina et al. (1997) indicate that, for potential CAS visual displays to be compatible with normal eye movement patterns, both rearview (center) and side mirror locations should be considered. A CAS display (e.g., a "do not go" light) could potentially be placed within one of the previously mentioned mirrors. Such a display might fit well with the hypothesized last glance that drivers normally make prior to lane change initiation – a glance to the rear view or side mirror. Head-up displays (HUD) might be considered as well since drivers

spend much of their time looking at the forward view (Mourant et al., 1969; Tijerina et al., 1997). In fact, Honda has developed an experimental blind-spot warning system in which a HUD presents vehicle location, distance, and relative velocity (range-rate) information, and issues auditory warnings if necessary (Yoshioka, Nakaue, & Uemura, 1999; Yoshioka, Uemura, & Nakano 1998). Such displays could be created via the use of lights (e.g., light beams or light-emitting diodes) installed on or near the dash that reflect upwards onto the windshield, similar to what was done by Recarte and Nunes (2003) to create their “virtual targets.”

Eye glance patterns might also indicate driver intention. For example, if a large proportion of glances are directed towards the right mirror and rearview mirror, this may indicate that a right lane change is about to occur. Such information could be useful for a CAS that would monitor driver eye movement to predict lane change direction and initiation. In terms of evaluation of potential CAS, the Recarte and Nunes (2000) approach, which uses dashboard mounted cameras to monitor detailed pupil action, may be useful for comparing baseline driving to lane changing. In addition, normal glance patterns and glance durations could be compared among drivers in which a CAS was available.

Effect of Traffic

Traffic is also likely to affect eye glance and lane change behavior. Bhise, Meldrum, Jack, Troell, Hoffmeister, and Forbes (1981) conducted field studies on public roads to investigate mirror glance times (eye position and head movements) during lane change maneuvers. Participants followed a pickup truck and were instructed to make lane changes in various levels of traffic (i.e., with and without an overtaking vehicle present). It was found that glance durations increased by an average of 0.25 s with the presence of traffic (when an overtaking vehicle was present), as compared to situations with no traffic. Single glance durations were between 1.1 s and 1.8 s ($M=1.25$ s) when there was no overtaking traffic in the adjacent lane, and 1.0 s to 2.3 s ($M=1.5$ s) when there *was* overtaking traffic in the adjacent lane. Robinson et al. (1972) reported that the mean visual search time for preparing for a lane change varied with and without traffic. Overall, traffic causes a large (50 to 85%) increase in both total and visual input times. Without traffic, visual search times were 3.7 s for left lane changes and 3.4 s for right lane changes. With traffic, visual search times were 6.1 s for left changes and 4.5 s for right lane changes. In addition, mirror-glance style was characterized for each participant. For example, most participants glanced at the left outside mirror and often at other locations before changing lanes. Most participants tended to maintain a glance style throughout the experiment. Such information might be useful in estimating the timing and duration of a warning to be presented during latency.

Lane Change Sequence

The sequence for a lane change made from the right lane into the left lane due to a slow vehicle ahead is presented based loosely on Chovan et al. (1994) and Wierwille (1984), as illustrated by Figure 2.6. It represents a somewhat idealized maneuver; however, it may aid in understanding the processes involved. In Figure 2.6, SV refers to the subject vehicle, POV_L refers to the lead principal other vehicle, and POV_F refers to the following POV. POV_{LO} refers to the lead POV in the original lane, and POV_{FO} refers to the following POV in the original lane; POV_{LD} refers to the lead POV in the destination lane, and POV_{FD} refers to the following POV in the destination lane. SV- POV_{FD} refers to the gap between vehicles, as in “SV to following POV

in the destination lane;” $SV-POV_{LO}$ refers to the gap between the SV and the lead POV in the original lane, and so on (Jula et al., 1999).

The driver scans the vehicle’s mirrors, noting the number, position, and range-rate of surrounding vehicles. This is done in an effort to collect information that is required of a driver making a successful lane change. Just before the driver decides to initiate a maneuver, a final visual check, either in the mirror and/or over the shoulder, is made. A go/no-go decision is then made. If a go decision is made, the initial steering wheel input occurs, usually in conjunction with a turn signal. If a no-go decision is made, the driver maintains his or her current position, or adjusts his or her position accordingly until a go decision can be reached. When a go decision is made, the lane change is initiated.

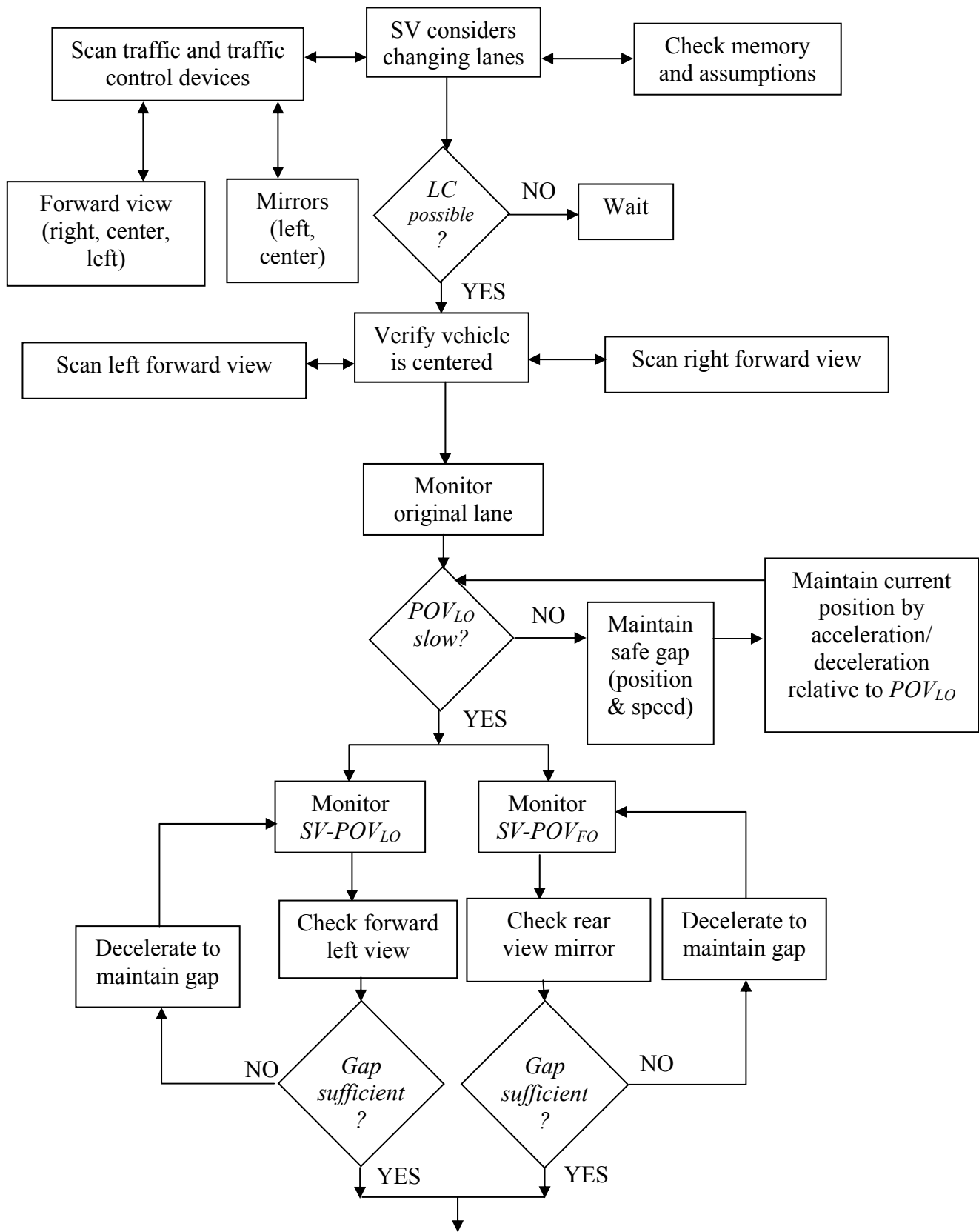


Figure 2.6. Lane Change Event Sequence Diagram – Right Lane to Left Lane.

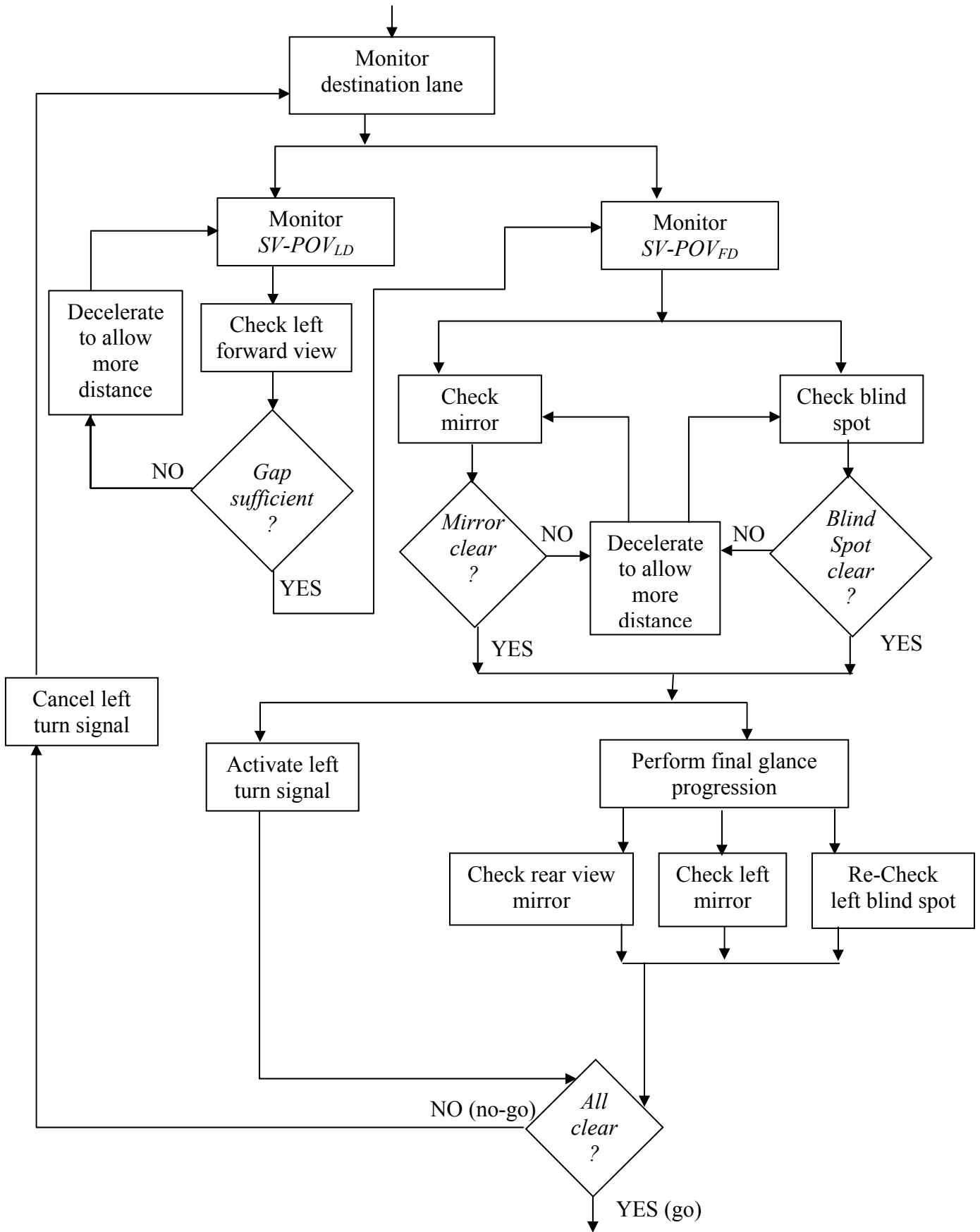


Figure 2.6. Lane Change Event Sequence Diagram (cont.).

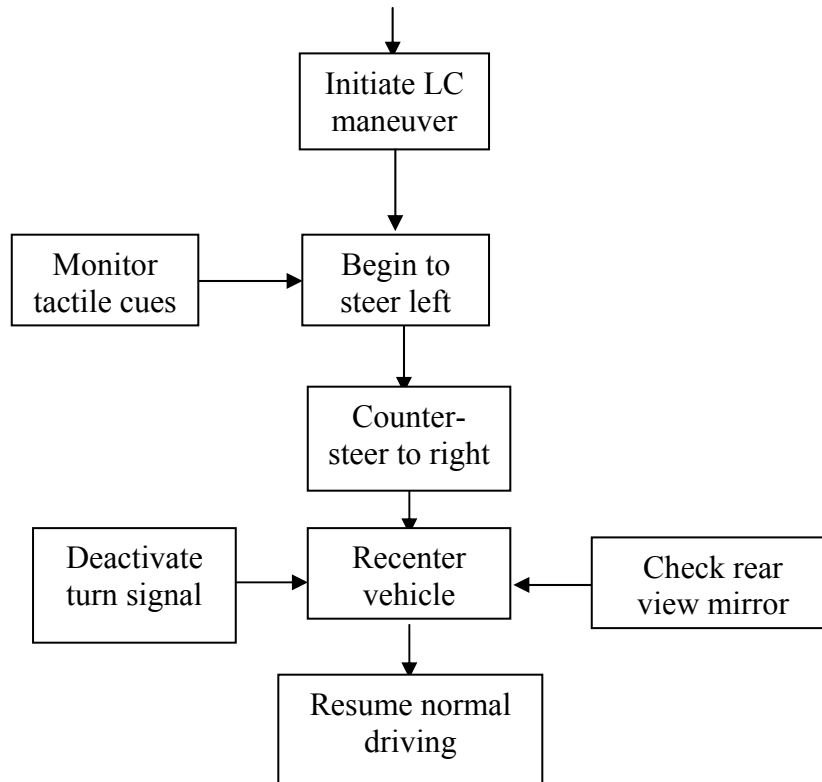


Figure 2.6. Lane Change Event Sequence Diagram – Right to Left Lane (cont.).

A Continuum of Research Designs

Various research designs exist along a continuum, with experiments ranging from those performed in a laboratory setting to naturalistic observation conducted in real-world settings, as illustrated by Figure 2.7.

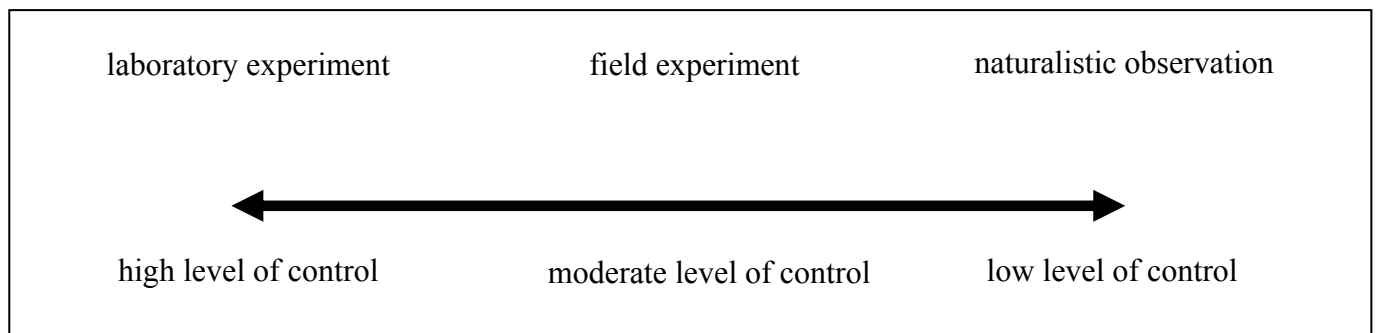


Figure 2.7. Continuum of Research Designs.

The laboratory setting is used to manipulate an independent variable, while also attempting to hold all other extraneous variables constant across groups to prevent confounding. Various experimental methods can be used, such as those classified by Leedy (1997). He

describes experimental studies of four types: 1) pre-experimental designs, including case studies and single group pretest-posttest designs; 2) true experimental designs, including pretest-posttest control group designs; 3) quasi-experimental designs, in which random selection and assignment are not possible (e.g., nonrandomized control group pretest-posttest design, time series); and 4) correlational (attempts to establish cause-effect relationships) and ex post facto (“experimentation in reverse”) designs. The other extreme is naturalistic observation, which has no control or variable manipulation.

Naturalistic observation involves observing participants as they behave in a natural setting, without experimental control of behavior and without making the observer’s presence known (Fernald, 1999; Keppel, Saufley, & Tokunaga, 1992). In this way, normal behaviors can be observed (Goodwin, 1995; Suen & Ary, 1989). During naturalistic observation, there is no intervention on behalf of the experimenter, and the researcher simply observes participants without manipulating any variables. In the scientific world, this type of research is very valuable as a first step because it provides the researcher with an understanding of the natural state of events. From there, the researcher often develops hypotheses about the relationships between variables in the environment.

Towards the middle of this continuum of research designs is the field experiment. Field experiments combine elements of laboratory experiments and naturalistic observation. Like other types of experiments, a field experiment requires that the researcher manipulate one or more independent variable(s) while attempting to hold other variables constant. However, since a field experiment is often performed in a natural setting, less control over extraneous variables is maintained. For example, the setting itself cannot be controlled (e.g., other traffic). In addition, participants are not randomly assigned to conditions. However, results are more likely to be applicable to real-world situations. That is, field experiments trade internal validity for greater external validity.

This dissertation involved using data collected during a field experiment that was conducted on actual roadways. This experiment contained aspects from both ends of the previously mentioned continuum. Control of which participants were assigned to each condition was maintained via a balanced design. In addition, drivers were instructed to drive the experimental vehicles only to and from work, and not to use the vehicle for personal use (e.g., on the weekend). Much effort was put forth to make the driving experience as close to “normal” as possible. As compared to previous research efforts, it is believed that this field experiment recorded driving behavior that was quite representative of regular, day-to-day driving. The data collection equipment was unobtrusive. Drivers were instructed to drive as they normally would and to follow their normal route. Finally, since drivers had each vehicle for an extended period (i.e., 10 business days), drivers were likely to become familiar with the vehicle. As a result, the driving behavior that was observed was very close to matching the behavior that would have been observed had the driver been driving his or her own vehicle. In fact, in most cases drivers displayed behaviors that indicated they were very comfortable while driving the experimental vehicles (e.g., singing, grooming, using cell phones).

In this sense, the study being described was a type of quasi-experimental design (Leedy, 1997). That is, due to the need for participants to meet particular criteria (e.g., solo drivers, willingness not to wear sunglasses, need to drive particular route), true random assignment and selection was not possible. In addition, a separate control group was not included, as is typically done. In this case, participants essentially served as their own controls in what is often referred to as a *crossover* design (Mason, Gunst, & Hess, 1989), at least in the case of comparing baseline

(straight-ahead) driving with lane changing. That is, the baseline segments were selected so that each of the 16 drivers had at least 2 events in the set of 40 baseline segments; these segments were selected at least 60 seconds before an actual lane change event, during a period when no lane change was taking place. Also, elements of a true experimental design were included, in that driver performance comparisons between groups of drivers (e.g., highway vs. interstate drivers) were designed into the field experiment.

Naturalistic Observation and the Field Experiment

Both naturalistic observation and field experiments can take place in a natural environment. Each has the advantage of gathering realistic data from actual settings. However, there are two main differences between naturalistic observation and a field experiment. First, with naturalistic observation, there is no intervention on behalf of the experimenter, while in a field experiment, the dependent variable(s) is collected or coded by the experimenter and independent variables are manipulated. Second, in naturalistic observation, participants are unaware that they are being observed. In a field experiment, participants have given their consent to be a part of the experiment and are aware that their behavior will be observed or otherwise recorded.

A disadvantage of both of these data collection methods is the time and effort required to convert raw observational information into usable behavior measures. Analysis of data usually takes five to seven times the amount of time spent recording events and may require access to specialized recording and playback equipment (Kirakowski, 1997). Analysis may also involve creating additional operational definitions to categorize observations of interest, or it may involve the use (or creation) of database interfaces or analysis software. This effort can be limiting, since rich, complex behaviors must be described in simple terms to fit into a relatively small set of categories or definitions. In addition, the training of experimenters can be time intensive. Finally, for both data collection and data analysis, training is necessary to minimize individual differences among experimenters. However, despite the time and effort required for dealing with such data, budgeting for appropriate resources will allow these data to be analyzed and used to conduct useful research.

A potential disadvantage of the field experiment observation technique is experimenter presence. Data collection can be intrusive, and participants may alter their behavior due to the presence of an experimenter. A naturalistic observation experiment is one in which the participants are *not aware* that they are being observed. For the case in which the participant is aware that they are being observed, it is possible that behavior may be modified. For example, a classic observational study of productivity was conducted in Western Electric's Hawthorne plant near Chicago, Illinois. Researchers discovered that their own presence had a positive influence on productivity (i.e., the Hawthorne Effect). As long as the experimenter was present, workers altered their behavior (i.e., increased productivity) (Homans, 1927). Gardner (2000) discusses the issue of experimenter presence in the context of observing families in their homes while conducting social psychology observations. According to Gardner, it appears that experimenter presence may initially influence behavior. However, this effect tends to decline over time as participants habituate to being observed. Homans' work (Homans, 1927) indicated that workers continued to alter their behavior as long as the experimenter was present for many weeks. In each of these cases, another person was actually present while the experiment took place. It is possible that experimenter presence could be eliminated if observations could be made using other means.

Using Video

The logistics of conducting live observations, recording those observations, and placing an experimenter in an amenable observation location may be difficult. However, the use of video for recording behavior provides a possible solution to address the issue of experimenter presence. While little is known about the reactive effects of video, the effect may be less than with live observers. Gardner (2000) cites research cases in which audiotape or videotape observation was very unobtrusive. Thus, it is logical to use video cameras to record driver behavior in a similar manner. Video has been used extensively for recording driving behavior (Bhise et al. 1981; Burger et al., 1980; Grace, Byrne, Bierman, Legrand, Gricourt, Davis, Staszewski, & Carnahan, 2001; Hetrick, 1997; Mourant & Donohue, 1974; 1977; Mourant, Rockwell, & Rackoff, 1969; Mourant & Rockwell; 1970; 1972; Recarte & Nunes, 2000, Rockwell, 1988; Wierwille et al., 2000). However, in most of these studies, the equipment was somewhat intrusive. Tijerina (1999) was one of many researchers who suggested a need for on-road studies with instrumented vehicles and unobtrusive surveillance. For example, NHTSA has supported this philosophy with the development of systems such as the Data Acquisition System for Crash Avoidance Research (DASCAR) and MicroDAS, “a relatively inexpensive derivative portable system” (Allen et al., 1999, p. 4), designed to be unobtrusive and inconspicuous (NHTSA, 1994; Barickman & Goodman, 1997) A similar system, introduced by Rockwell and Snider in 1965 called DIARS [Driver Instrumentation and Recording System], was designed “to collect field data that permits elimination of biases associated with the presence of an experimenter” (Warner, 1970, p. 212). In alignment with this philosophy, a similar approach was taken to collect video and sensor data to be analyzed in this study. The manner in which recording equipment was used for data collection will be further discussed in the method section.

Driving Field Experiments

This data collection effort was, by definition, a field experiment, in that participants were selected to fit into categories (i.e., the within-subjects variables of route, usual vehicle [vehicle normally driven], and gender), and the between-subjects independent variable experimental vehicle was manipulated (i.e., all participants drove both the SUV and the sedan). Constraints also existed in participant selection. For example, drivers were selected who commuted on either the interstate (I-81/I-581) or a US highway (US Route 460/Route 11), who did not carpool, and who were willing to drive without wearing sunglasses (so the camera could capture eye glance location). Given such constraints, however, it is believed that participants behaved in a realistic manner after habituation (i.e., close to how they might behave if naturalistic observation was possible in this context), since experimenter interaction was minimal (in most cases, participants only interacted with the experimenter to arrange vehicle pick-up/drop off). Also, the cameras and radar equipment were unobtrusive; it is likely that drivers essentially forgot they were being monitored while driving, as verified by review of the video. No feedback was given to the driver to indicate that they were being recorded (i.e., all data collection equipment was locked in a storage unit in the truck), and none of the cameras and radar sensors was visible while driving. The exception was the driver’s face camera that was mounted unobtrusively in the A-pillar (see Figure 3.6) of the vehicle.

For these reasons, the experimental design allowed drivers to behave quite normally, as compared to previous driving research efforts. These previous efforts suffered the limitations imposed by experimenter presence and obtrusive equipment. In comparison, driving field experiments attempt to capture driving in a near-natural context. One such experiment involved

monitoring local/short haul truck drivers during their work day (Hanowski, Olson, Perez, & Dingus, 2001). Participants drove company trucks instrumented with video cameras and sensors so that data could be collected on the incidence and characteristics of distracting activities. Other driving studies have been conducted, such as for the case of investigating the safety of Intelligent Cruise Control (ICC) systems in passenger vehicles (Fancher et al., 1998). Further, according to Barr, Yang & Raney (2003, p. 3):

The U.S. Department of Transportation (DOT) has sponsored several studies involving the collection of . . . data on car and truck drivers by instrumenting their vehicles or supplying instrumented vehicles for them to use as their personal vehicles on public roads.

Previous researchers have suggested the use of methods in which drivers are observed and recorded unobtrusively:

- Robinson, Erickson, Thurston, and Clark (1972) concluded that measurements taken without the driver's awareness ought to be considered for studying the visual search problem while driving.
- Staplin, Lococo, Sim, and Gish (1998), and Tijerina et al. (1996) recommended that data could be gathered under a wide range of natural driving conditions using unobtrusive observation.
- Llaneres, Freedman, Steinberg, and Perel (1999) stated that "driver behavior in actual operational settings must be studied . . . to support the development and evaluation of in-vehicle systems (p. 5)."
- Tijerina (1999) suggested that studies of "plain old driving" are needed, including on-road studies with instrumented vehicles and non-obtrusive video surveillance.

The current field experiment is a best attempt at collecting data on "plain old driving." This field experiment included elements of a laboratory experiment in which independent variables were manipulated and dependent measures collected. In addition, this field experiment was conducted in a manner that would capture driving behavior that was very close to natural behavior. Specifically, the experiment attempted to minimize participant-experimenter interaction by using unobtrusive data collection equipment and collecting data over a long period (i.e., 20 days of commuting to and from work). In comparison to previous driving research in which drivers were aware of data recording due to obtrusive cameras and hardware, while simultaneously being instructed when to maneuver by an experimenter, the field experiment described here was believed to be quite natural for participants. For this reason, it is believed that this field experiment collected data that were highly representative of driving behavior performed in a realistic, on-road setting, under minimal constraints.

Lane Change Research Needs

This literature review has provided valuable insight into the types of research that have been conducted into the lane change maneuver. There are numerous areas in which the research is lacking, and this has provided direction for this study. Some of the areas in need of further research include the following:

1. There is a lack of field data collected under natural conditions. Most data were gathered with an experimenter present, under controlled settings, with obtrusive equipment, and for short durations. Participants were unlikely to drive in a natural manner under such conditions, and thus, the results of these studies should probably not be generalized as representative driving behaviors.
2. There is a need for better understanding of glance patterns as a function of criticality of the maneuver and presence of a vehicle ahead.
 - Do eye glances follow a specific pattern during lane change latency across participants?
 - a. If so, can this information be used to help determine the location and design of a lane change CAS?
3. There is a general lack of information about types of lane changes, their relative frequencies, and the duration of lane changes, especially as they occur without an experimenter present (as opposed to being performed as instructed by an experimenter). Such information could provide insight as to when and under what circumstances a lane change CAS might be most useful.
4. There has been a lack of lane change data for certain environments such as:
 - US highway vs. interstate.
 - Suburban/rural vs. urban roadways.
 - Hilly terrain (most data has been collected on flat roads).
5. There are no data as to what differences may exist for lane change behavior for various types of vehicles, such as between SUVs and sedans.
6. CAS designers lack fundamental information required for effective lane change CAS design, such as:
 - What are the most prevalent glance locations of drivers who are preparing to make lane changes?
 - When and under what circumstances do drivers look at particular mirrors/locations?
 - Do drivers reliably use their turn signals during latency, and if so, can this be used to trigger a lane change CAS?
7. Data on lane changes can be analyzed to develop the foundation of a predictive CAS algorithm model:
 - How can lane change initiation be predicted?
 - What variables are relevant for developing predictive models?

The data analysis effort for this dissertation was designed to fill in as many of these data and information gaps as possible so that future researchers and designers would have a more complete picture of lane change behavior when a slow lead vehicle was present. The next chapter describes this experimental design and the data collection and analysis procedures.

CHAPTER 3. METHOD

This section describes the experimental methods used in three phases of investigation, including data collection, identifying and categorizing all maneuvers, and categorizing a sampling of maneuvers in depth. The approach for this research was to access a large database of highway data that was collected using instrumented vehicles and ordinary commuting drivers. The vehicles gathered data automatically; no on-board experimenter was needed. The instrumentation was unobtrusive and required no attention by the driver. The gathered data were then examined for lane changes with a slow lead vehicle present.

Data Collection

Participants

Sixteen drivers who normally drove 25 or more miles in each direction to and from work were recruited to obtain a representative sample of drivers and lane-changing behaviors. One group consisted of eight drivers who commuted daily on Interstate 81, Interstate 581, or a combination of these two interstates in southwestern Virginia (e.g., between mile markers 100 and 150). The other group was comprised of eight commuters in southwestern Virginia who traveled on US 460, US 11, or a combination of the two highways. Half of each group of eight ordinarily drove an automobile to and from work, while the other half ordinarily drove an SUV, van, or pickup truck. Participants were between 20 and 64 years of age ($M = 40.8$, $SD = 12.2$), with equal gender representation in each subgroup. Each driver drove each of two research vehicles for ten business days, for a total of twenty days of driving for each participant and a grand total of 329 days of lane change data. The order in which the participants drove the research vehicles was counterbalanced in each subgroup of four drivers. Participants received \$10/day for each day of driving and were reimbursed for gasoline. Participation was determined after screening and selection criteria were met, as described in the Experimental Procedure subsection.

Experimental Design

The research design that was used for the data collection of driving behavior is shown in Figure 3.1. The study was a mixed factorial design. There were four independent variables: route, usual vehicle, gender, and experimental vehicle. The between-subjects independent variables of the experiment were: route (interstate or highway), usual vehicle (sedan driver or SUV driver), and gender. Experimental vehicle (experimental sedan or experimental SUV) was a within-subject independent variable. For clarification, usual vehicle refers to the vehicle normally driven by the participant, whereas experimental vehicle refers to the two instrumented vehicles driven for the experiment.

Table 3.1 shows how counterbalancing was accomplished for experimental vehicle (i.e., whether the sedan or SUV was driven first). Note that route, usual vehicle, and gender were between-subjects variables and had no effect on counterbalancing. However, participants were introduced into the experiment in the order shown in Figure 3.1 and Table 3.1 to the extent possible. The purpose of introducing participants in this manner was so that no one combination of usual vehicle followed a driver of the same type (e.g., a female/sedan/interstate driver did not follow another female/sedan/interstate driver in the experiment). In both Figure 3.1 and Table 3.1, M designated a male driver and F designated a female driver.

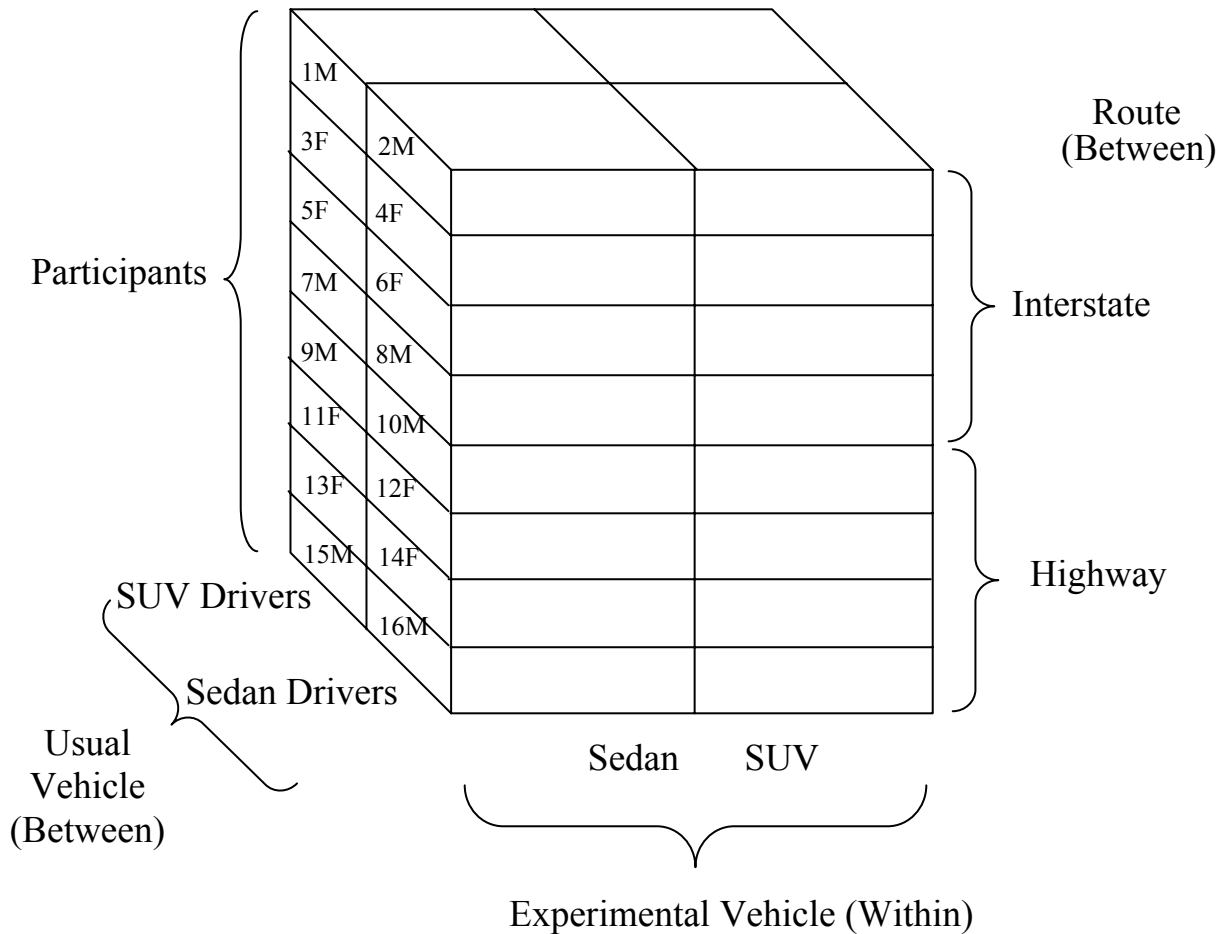


Figure 3.1. Experimental Design.

Table 3.1: Counterbalancing of Participants.

Driver Type	Vehicle Driven First	Route			
		Interstate		Highway	
SUV Drivers	Sedan First	1M	5F	9M	13F
	SUV First	3F	7M	11F	15M
Sedan Drivers	Sedan First	2M	6F	10M	14F
	SUV First	4F	8M	12F	16M

Independent Variables

All independent variables are listed in Table 3.2. The interstate route, I-81 in southwestern Virginia, was selected because it represents a situation where lane changes are required and problematic; it is a heavily traveled rural interstate with hills and many heavy vehicles. Drivers on the interstate also often drove a portion of their route on I-581, a heavily

traveled spur route leading into downtown Roanoke, Virginia. The highway route included both US 460 and US 11. These roads require lane changes at somewhat slower travel speeds (e.g., 45 to 55 mph), are largely 4-lane (2 in each direction), and are generally not access controlled.

As a reminder, usual vehicle refers to the *vehicle normally driven by the participant*. Participants were separated into two groups: those who ordinarily drove an automobile to and from work; and those who ordinarily drove an SUV, van, or pickup truck. Usual vehicle is not to be confused with experimental vehicle, which refers to the actual vehicle driven during the study (all drivers drove both the SUV and the sedan). In terms of gender, half of the participants were males and half were females. Information about age, while not used as an independent variable, was also collected.

Table 3.2: Independent Variables.

Independent Variable	Levels
Route	Highway or Interstate
Usual Vehicle	Sedan Driver or SUV Driver
Gender	Male or Female
Experimental Vehicle	Sedan or SUV

Apparatus

The two instrumented vehicles (Figure 2.2) were a sedan (1999 Ford Taurus) and an SUV (2000 Ford Explorer). These vehicles were selected because they have substantially different rear and side visibility characteristics. For example, the sedan has relatively “thick” C-pillars resulting from the use of the elliptically shaped rear windows. The back end of the passenger compartment is also a bit high. These factors could lead to small compromises in over-the-shoulder visibility, particularly for shorter drivers. The SUV is a tall vehicle with larger windows. It thus has relatively good visibility to the sides and rear. The SUV also has larger side view mirrors. In addition, because of the drivers’ seated height differential, the SUV provided better visibility over lead vehicles on the forward roadway.

Each vehicle was equipped with a data collection system composed of unobtrusive hardware and software systems to collect data automatically, eliminating the need for a ride-along experimenter. The inconspicuous instrumentation in the vehicle allowed drivers to forget that it was present. It was believed that once drivers adapted to the vehicles, they would exhibit natural, or unmonitored, behavior. Three data collection systems were used to collect data in an integrated, automated, unobtrusive manner: a video system, a sensor system, and a radar system. Resulting data were stored in a locked storage unit located in the rear area of each vehicle.



Figure 3.2. Research Vehicles.

Video System

A video data collection system was used to capture relevant video data while driving. The video data collection system included five-channel video using miniature cameras, as illustrated by the schematic of camera locations and fields of view in Figure 3.3. Each camera was a monochrome charge coupled device (CCD) weighing about 1 ounce, 10 mm wide, with a fixed focus lens. The forward camera (Figure 3.4) was mounted behind the rear view mirror inside the vehicle to provide a view out of the windshield corresponding to the view the driver might see when looking forward. A rearview camera (Figure 3.5) was mounted outside, above the rear window. Another camera was mounted inside the vehicle within the A-pillar (Figure 3.6), pointing toward the driver's face, to provide a view of the driver's eyes and head. Cameras were also placed outside of the car, under each of the two side mirrors (Figure 3.7) to provide views of the area adjacent to and behind the vehicle, including what the driver might see when looking into the mirror. These latter two cameras also included coverage of the lane lines.

The outputs of the five cameras were combined using two quad splitters. The first splitter combined the two side-camera images into a single image as depicted in Figure 3.8. The output of this splitter was combined with the other three outputs using a second quad splitter. The resulting composite 5-camera image is shown in Figure 3.9. Note that the lower-right image is based on images from the two outside mirror cameras, divided vertically at the center.

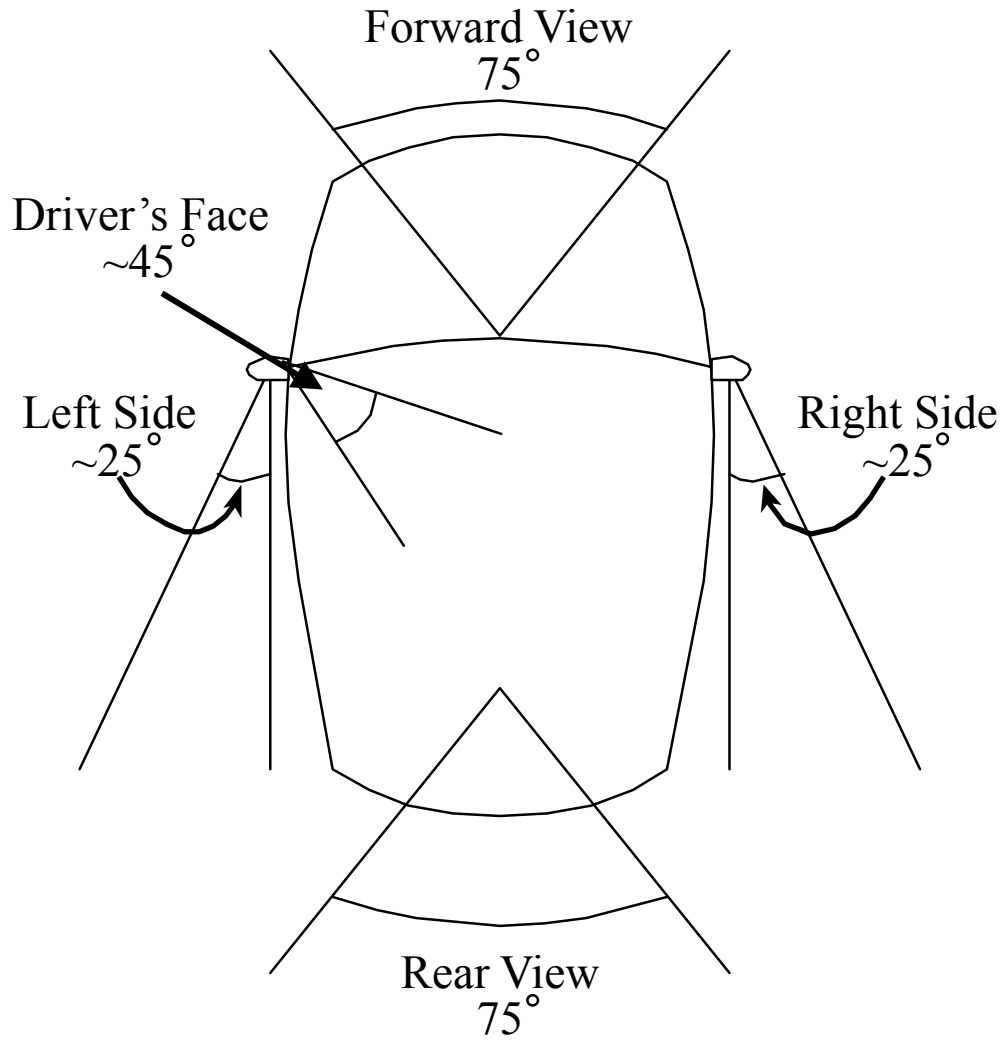


Figure 3.3. Video Camera Locations and Fields of View.



Figure 3.4. Forward View Video Camera Behind the Rear View Mirror.



Figure 3.5. Rear View Video Camera Above the Rear Window.



Figure 3.6. Driver's Face Camera Mounted within the A-Pillar.



Figure 3.7. Camera Mounted Under the Side Mirror.

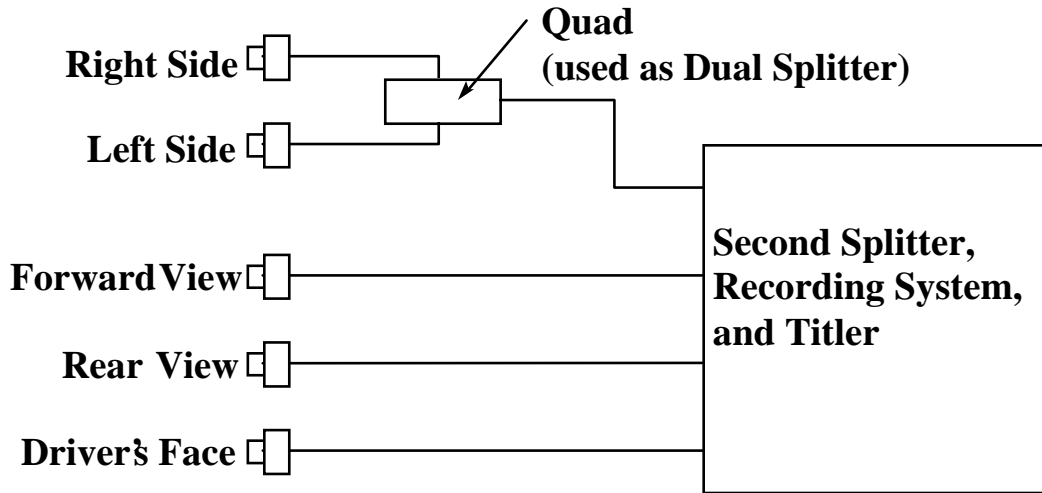


Figure 3.8. Video Diagram Showing use of Quad Splitters.

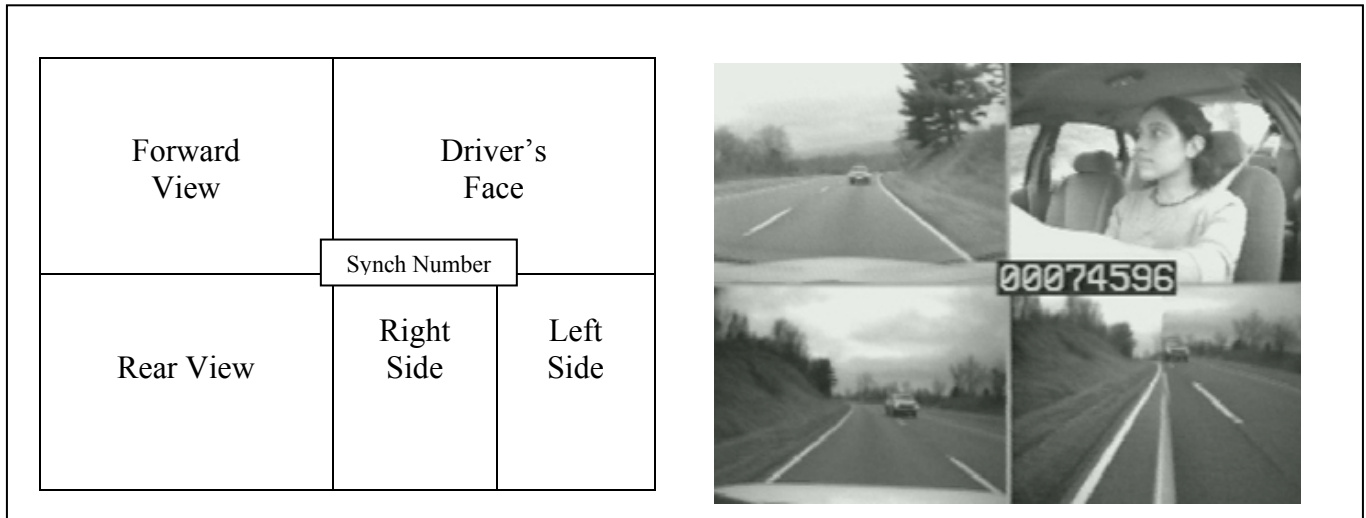


Figure 3.9. Image Arrangement on Quad-Split Screen.

Vehicle Parameter Sensor System

The vehicle parameter sensor system included a series of sensors placed throughout the vehicle to collect data, such as steering wheel position, SV velocity, and turn signal activation. The sensor system was developed by the Hardware Engineering Laboratory at the Virginia Tech Transportation Institute (VTTI); it is based on earlier versions of the system, which was originally developed to investigate safety issues in local and short haul trucking operations (Hanowski et al., 2000). Data collected from this system were synchronized to other data by a time-stamp (or *synch number*, also shown in Figure 3.9) so that files could be compared using time as an anchor. Synch numbers were recorded in tenths of a second.

Radar System

The vehicle parameter sensor system also interfaced with the radar system, which consisted of three Eaton Vorad EVT-300 radar units. These units were installed on each research vehicle as illustrated by Figure 3.10. The Eaton radar is a Doppler radar with a 12-degree angle of coverage to monitor other vehicles up to a range of about 350 feet (Eaton, 2001). It has been used mostly on semi-tractor trailer trucks as a collision warning system to warn drivers when vehicles are present. For the data collection effort, the radar system was used in an unobtrusive manner, and the driver was not aware that radar data were being collected. Radar units were installed on the outside of the vehicle (as pointed out to participants during the orientation). However, these units were not visible to the driver while seated in the vehicle. One radar unit was installed in the front bumper facing straight forward (Figure 3.11), and the other two units were installed at the back of the vehicle facing rearward (Figure 3.12) and offset by 6 degrees from the longitudinal axis. These units were configured in this manner so that range and range-rate to vehicles interacting with the instrumented vehicle could be determined.

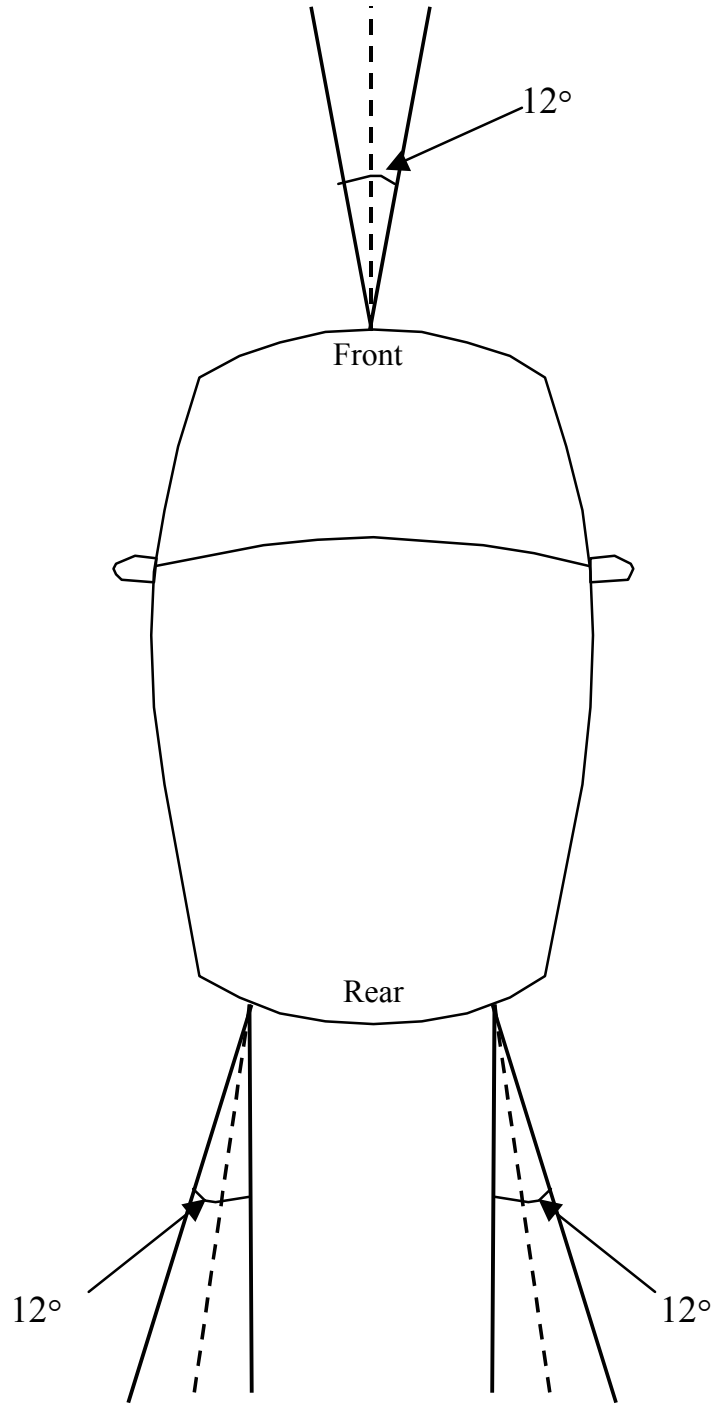


Figure 3.10. Radar Locations and Effective Angles of Coverage.



Figure 3.11. Front Radar Unit.



Figure 3.12. Rear Radar Units.

Data Collection System

The data collection system hardware, including two high-8 videocassette recording devices, central processing unit, zip drive, keyboard, quad splitters, titler, antenna, and harness bundle, was mounted so as not to be visible to the driver. The video recording devices collected video data using a titler to place a time stamp on each frame of video data collected. The central processing unit combined data from both the vehicle parameter sensor system and the radar system. Data files, including data from both of these systems, were created for analysis in conjunction with the video data. A storage unit (Figure 3.13) was constructed to house various components of the data collection system. A storage unit containing the data collection system

was placed in the trunk of the sedan and in the rear area behind the rear seat in the SUV, where it was locked by the experimenter. The unit was very unobtrusive but allowed the experimenter to gain access to the hardware systems to change tapes and download computer data files.



Figure 3.13. Data Collection Systems Storage Unit.

Dependent Variables

The vehicles were instrumented to collect various types of data. Video data included eye behavior for the driver of the SV; the location and duration of eye glances prior to and during lane changes were later extracted from the video data. Sensor data included driver-vehicle performance variables such as steering wheel position, velocity, and turn signal use. Radar data provided inter-vehicle variables related to lane changing. These data included the range, range-rate, and angle of surrounding POVs in relation to the SV. The position of POVs was categorized relative to the SV (e.g., front, rear left, rear right) and then for each position, by azimuth (angle) from the SV. Table 3.3 lists the dependent variables collected by the sensors within the vehicle or calculated during data analysis.

Table 3.3: Dependent Variables

Dependent Variable	Unit/level
Lane Change Duration	Seconds (End Sync minus Start Sync/10)
Severity	7 point scale (1 = unconflicted, 7 = physical contact)
Urgency	4-point scale (1 = not urgent, 4 = critical)
Direction	Left (L) or Right (R)
Velocity	Mph or ft/sec (for SV or POV)
Range	Feet
Range-Rate or Relative Velocity (ΔV)	mph or ft/sec (difference between vehicle velocities)
Time-to-Collision (TTC)	Seconds (Range/ ΔV)
Steering Wheel Position (Azimuth)	Radians
Brake Pedal Use	0 = off, 1 = on
Lateral Acceleration	gs at t_0 (negative indicates moving right)
Eye Glance Position	Discrete position (forward, left mirror, blind spot, etc.)
Turn Signal Use	0 = off, 1 = right on, 2 = left on
Turn Signal Timing	Time in seconds that the signal was activated (negative values indicated the signal was activated before t_0)

Eye Glance Position

Eye glance position is the location in which the driver looked during the lane change. Particular emphasis was placed on the three seconds just prior to the lane change (lane change latency), since critical driver decisions must be made during that time period (Lee, Olsen & Wierwille, 2003) and distinct scanning patterns are apparent during that period (Salvucci, Liu, & Boer, 2001). Discrete positions included forward, rearview (center) mirror, left mirror, right mirror, left window, right window, left blind spot, right blind spot, and instrument cluster.

Steering Wheel Position

The position of the steering wheel was monitored at all times during data collection. Position was measured in radians (rads), a unit of plane angular measurement determined by the requirement that there are 2 rads in a circle. Thus, 2 rads equals $360/\pi$ degrees. This means that 1 rad = $180/\pi$ degrees, and 1 degree = $\pi/180$ rads. Since $\pi/180 =$ approximately 0.017, 1 degree = approximately 0.017 rads, 3 degrees = 0.052 rads, 12 degrees = 0.209 rads, and so on.

Maneuver Type

Eleven categories of maneuvers were identified such as shown in Table 3.4. Each maneuver type was associated with the motivation for the maneuver. For example, the merging vehicle maneuver indicated that the driver made the maneuver because a vehicle ahead was merging onto the roadway. For this research effort only slow lead vehicle lane changes were investigated. Slow lead vehicle refers to lane changes made as a result of a slow vehicle ahead in the same lane as the SV.

Table 3.4: Maneuver Types and Descriptions.

Maneuver Type	Description
Slow lead vehicle	Lane change to pass a slower vehicle so the SV could maintain speed.
Return	Lane change to return to preferred driving lane.
Enter	Lane change to enter road (e.g., from on-ramp).
Exit/prepare to exit	Lane change associated with exiting.
Tailgated	Vehicle tailgating/approaching quickly.
Merging vehicle	Vehicle entering roadway causing SV to change lanes.
Rough/obstacle avoidance	Maneuver to avoid obstacle or rough road surface.
Lane drop	End of driver's lane (e.g., road goes from 3 to 2 lanes).
Added lane	Addition of a lane (e.g., road goes from 2 to 3 lanes).
Unintended	Unintended lane deviation (e.g., distraction in car).
Other	Lane change for any other reason or for no discernible reason.

Success/Magnitude

The success/magnitude dependent measure had four categories: single lane changes, passing maneuvers (a series of 2 single lane changes to pass a vehicle, made within 45 seconds), multiple lane changes (more than 1 lane change completed in the same direction [e.g., crossing multiple lanes of traffic]), and unsuccessful lane changes (aborted lane change, unintentional lane change, or partial lane change). In terms of the success/magnitude measure, single lane changes and only the first portion of passing maneuvers were used-- this dissertation was only interested in the period leading up to the lane change. That is, for all lane changes, the segment leading up to t_0 (lane change start) was analyzed. Passing maneuvers, which consist of two lane changes, were included, but only the first lane change was analyzed. The return maneuver was not relevant to this dissertation, in which slow lead vehicle lane changes were investigated.

Direction

Lane changes were categorized in terms of the initial direction of the lane change. For example, a lane change in which the SV moved from the right lane into the left lane was categorized as a “left” direction lane change because the movement was to the left. Additionally, a passing maneuver from the right lane into the left lane and back into the right lane was categorized as “left” because the initial movement was to the left.

Severity Rating

After data gathering, all lane change events were rated using the 7-point severity rating scale (1 = unconflicted, 7 = physical contact), which indicated the degree to which the vehicle in the destination lane was cut off (Table 3.5). Severity was rated based upon vehicle presence within the PZ (4 feet in front of the SV to 30 feet behind it) and time-to-reach the rear edge of the PZ for those vehicles within the FAZ (30 to 162 feet behind the SV), as described in Chapter 2 of this document. These zones refer to areas in the adjacent destination lane, beside and behind the SV, which should be monitored before lane change initiation (Talmadge, Chu, & Riney, 2000). The severity rating scale reflects conflict aspects of vehicle movement, where conflict is associated with vehicles in the adjacent lane when the driver of the SV moves into that lane. A lane change conflict, by definition, requires that there be a vehicle present in the lane into which

the driver of the SV wishes to move. In this case, level 7 of this scale pertains to physical contact between vehicle (none observed) and level 6 pertains to emergency or unplanned maneuvers required to avoid a collision. Levels 1 through 5 of the rating scale are related to other vehicles in the PZ (level 5), or within the FAZ and their relationship to the end of the PZ (levels 1 through 4). The severity scale was created based upon review of work by TRW, Inc. (Talmadge, Chu, Eberhard, Jordan, & Moffa, 2000) in which lane changes were classified into similar categories, as well as input received from discussions held with NHTSA personnel.

Table 3.5: Severity Rating Scale.

Rating	Description
7	Physical contact/collision occurs with a vehicle (or object) in the adjacent lane into which the driver of the SV was attempting to move (no incidents observed).
6	Emergency action/unplanned sudden maneuver required to avoid a collision with a vehicle (or object) in the adjacent lane into which the driver of the SV was attempting to move.
Ratings 5 through 1 were assessed <i>at initiation (Start Synch)</i> of the attempted lane change.	
5	POV in the proximity zone.
4	POV in the fast approach zone with time to reach closest end of zone, $T_r^\dagger, \leq 1.0$ sec.
3	POV in the fast approach zone with time to reach closest end of zone in the range $1.0 < T_r \leq 3.0$ sec.
2	POV in the fast approach zone with time to reach closest end of zone in the range $3.0 < T_r \leq 5.0$ sec.
1	POV in the fast approach zone with time to reach closest end of zone, $T_r, > 5.0$ sec, including case where there is no vehicle in the adjacent lane.

[†] T_r is the time required for a POV to reach the front end of the fast approach zone, the point 30 ft behind the SV.

Urgency Rating

Each lane change was also rated in terms of urgency. Urgency was rated on a 4-point scale (1 = not urgent, 4 = critical) that indicated how soon the lane change was needed based on the TTC with the closest vehicle ahead or behind for accelerating vehicles such as tailgaters; this is illustrated in Table 3.6. For example, for a slow lead vehicle maneuver with a TTC of 4.1 s, the urgency rating was 2 (urgent) because $5.5 \text{ s} \geq \text{TTC} > 3 \text{ s}$.

It is important to note the reason that two separate ratings were developed. The severity rating dealt with the situation in the destination lane, while the urgency rating dealt with the situation in the driver's current lane; both aspects were important in understanding driver behavior.

The remaining dependent measures, including velocity, acceleration, turn signal use, range, range-rate, TTC, and lane change duration, were either acquired via sensors or calculated during data reduction and analysis as needed.

Table 3.6: Urgency Rating Scale.

Rating	Description
4	<u>Critical incident/crash</u> : Physical contact/collision occurs with a vehicle (or object) in the same lane as the SV or the opposite adjacent lane; or a sudden maneuver (braking or swerving) is required to avoid such a collision (none observed).
3	<u>Forced</u> : The lane change has a high degree of urgency due to a short TTC* ($TTC \leq 3$ s) and/or close headway/tailway/distance to vehicle in the same or opposite adjacent lane.
2	<u>Urgent</u> : The lane change is somewhat urgent due to moderate TTC ($5.5 \text{ s} \geq TTC > 3 \text{ s}$) and/or moderate headway/tailway/distance to vehicle in the same or opposite adjacent lane.
1	<u>Non-urgent</u> : The lane change is not urgent, because of a minimal, infinite, or negative TTC ($TTC > 5.5 \text{ s}$) with a vehicle in the same or opposite adjacent lane, and/or long headway/tailway/distance, and/or lack of vehicles in the same or opposite adjacent lane.

* Time-to-collision is the time it would take for vehicles to collide if the rear vehicle did not maneuver. In other words, it is the time from the initiation (Start Synch) of the lane change to the time when the front bumper of the SV is parallel with the rear bumper of the POV (e.g., when the POV is in front of the SV), assuming constant velocity and acceleration.

Experimental Procedure

Participant Selection and Screening

One-page recruitment fliers describing the study (Appendix A) were posted throughout Blacksburg and Christiansburg, Virginia. The purpose of the fliers was to solicit volunteer participants for this study. Respondents contacted the experimenter and were screened over the telephone using the Telephone Driver Screening and Demographic Questionnaire (Appendix B). The experimenter used this form to document pertinent information about the potential participant. Only commuters who drove 25 miles or more on either Interstate 81 (or I-581) or select US Routes (460 or 11) were eligible. Other relevant information such as gender, route normally driven, vehicle normally driven, age range, medical and driving history, and use of corrective lenses and sunglasses was also reviewed during the telephone screening. After a series of screenings had been conducted, the process of selecting potential participants began. The experimenter reviewed all screening forms and selected those that met all criteria required. The forms were also reviewed by a senior researcher. Those drivers who qualified for the experiment were then contacted, and an appointment was set up for each driver to come to VTTI for orientation.

Participant Orientation

Participants were instructed to meet the experimenter at VTTI. Each participant reviewed the information recorded on the screening and demographic questionnaire for accuracy. Next, participants were asked to read and sign the Informed Consent Form (Appendix C), which included an overview of the study. After agreeing to participate, the driver's license of each participant was viewed to assure it was valid.

The next step involved each participant reviewing the Driving a Sport Utility Vehicle Form (Appendix D) and accompanying video. The video clip was recorded from the evening news and showed a demonstration of what could happen if an abrupt steering maneuver was performed while driving an SUV. The purpose of the form and the video was to raise participants' awareness of the differences between driving a sedan and an SUV. The driver was then shown the vehicle, including where the cameras and the data storage unit were located. The driver was seated in the vehicle, and the displays controls were reviewed to familiarize the participant with the vehicle. Finally, the participant conducted a test drive, during which the experimenter sat in the passenger's seat and gave verbal route instructions.

Driving Instructions

Participants were instructed to drive the experimental vehicle to and from work, as they normally would, in place of their regular commuting vehicle. Participants were reminded that running errands on the way to work, during lunch, and on the way home after work was permitted, but the vehicle was not to be used for personal use in the evenings or on the weekends. In addition, participants were reminded not to wear sunglasses or to carpool. Having an occasional passenger was permitted, however (e.g., during lunch). As stated in the Informed Consent Form, participants were to drive legally at all times.

Sequence of Data Collection

Each participant drove the sedan and then the SUV (or vice versa) for a total of 20 business days. The experimenter also coordinated the exchange of vehicles with the participant after the first ten days of driving. The participant did not need to be present during data retrieval since the experimenter knew where the vehicle was located. Data retrieval consisted of exchanging videotapes and downloading computer data onto zip disks for later analysis. The experimenter retrieved data and tested the system using a checklist. All tapes and Zip disks were labeled according to the conventions illustrated in the Analyst Training Manual (Appendix E). Once all days of driving were completed, the participant was instructed to return to VTTI and drop off the vehicle. While at VTTI, the participant was debriefed. During this debriefing, the participant was asked if he or she had any input regarding the study. Payment for the total number of days of participation and reimbursement for gasoline were provided at the end of the second experimental session (i.e., after the last 10 days of driving).

Data Reduction

Data reduction involved a series of steps described in the following sub-sections. A team of four data analysts, including the experimenter, identified and categorized each event. Training was a continuous process that began with an initial session in which data analysts reviewed the Analyst Training Manual (Appendix E). The manual provided operational definitions for start and end points, as well as for each of the ratings and categories used. The manual was developed by the author, who had several years of experience analyzing video behaviors, with input from two senior researchers. Training consisted of analysts reading the manual, followed by demonstrations of how to identify maneuvers. Each analyst spent time with an experienced analyst, learning how to operate the video tape player, categorize maneuvers, and enter data into the appropriate spreadsheet. Eventually, analysts were able to conduct data reduction independently, except for cases that were not clear, such as the case when the lane change type

was unknown or the start or end point was not easily discernable from the video image. Throughout the entire analysis effort, at least one experienced analyst was available at all times to answer any questions or review particular cases as needed, and analysts were instructed to seek input from other analysts or senior researchers. In addition, analysts were instructed to work a maximum of four hours per shift to maximize event-identification effectiveness and accuracy. Events were spot-checked by the experimenter, and other analysts spot-checked one another's work on occasion. Approximately 10% of all events were reviewed by two or more analysts for consistency.

The entire population of maneuvers was first reviewed so that a representative sample could be obtained for an in-depth analysis, as part of another research effort (Lee, Olsen, & Wierwille, 2003). Each lane change maneuver was identified by reviewing the videotapes. The data collection effort resulted in a total of 8,667 events, consisting of 11 lane change types. Each of these events was identified, categorized, and rated. Thereafter, a general analysis was performed on all 8,667 events, and an in-depth analysis was performed on the sample of selected events. A data integration program was used to integrate video, radar, and sensor data for each of the in-depth maneuvers. After each event was entered into this program, the event was ready for descriptive and statistical analysis. For this dissertation, a total of 3,227 slow lead vehicle lane changes (37.2% of the total: the single largest type) were available for analysis. This subset of was analyzed descriptively and then a sample was selected for in-depth analyses.

Identifying, Categorizing, and Rating All Maneuvers

As described, all lane change instances were identified in terms of specific initiation and end points. Each instance was then categorized and rated based upon training and the analyst training manual.

Initiation Point

An operational definition of the initiation point marking the beginning of a lane change or attempted lane change was required. This point is important because it represents the decision point (go/no-go) at which the driver decided to begin the lane change maneuver. In previous studies (Hanowski, Wierwille, Garness, & Dingus, 2000), the point in time representing the beginning of a lane change was defined by a combination of criteria. Experience indicates that drivers ordinarily return fixation direction to the forward view (i.e., from the mirrors or direct looks to the rear) when they begin the lane change. Initiation of the lane change itself can ordinarily be detected by a steering input or by movement toward the lane boundary or both. Steering movement is picked up by the steering sensor, and movement toward the lane boundary can be determined visually by the data analyst using the two side-mounted camera images of the recorded video. Thus, when time = zero (t_0), the beginning of the lane change or lane change attempt can be determined by monitoring one or more of the following:

1. The vehicle begins to move laterally relative to the lane.
2. Driver initiates a steering input intended to change the direction of the vehicle relative to the lane.
3. Driver returns gaze to the forward view after looking in mirrors or looking directly toward the side or rear.
4. The vehicle leaves the lane at least temporarily.

While four criteria were used to define the beginning point, they were often not all present. Thus, some judgment was necessarily required. In some cases, the driver may not look to the rear, and in other cases, the vehicle may naturally drift to the left or right without a steering input. Nevertheless, it was still possible for the reductionist to locate the initiation point in time by looking for the remaining criteria. In the case of the slow lead vehicle lane change, it was the first lateral movement toward the new destination lane that was used to identify t_0 , with the other cues serving as signs that the lateral movement was about to begin.

An additional cue that was sometimes present was the actuation of the directional signals. This signal alerted the reductionist to a possible lane change but could not be relied upon for determination of the start point. Signals are not always used, and when they are used, activation varied relative to the actual starting point. The activation point varied among drivers (Hetrick, 1997) and for the same driver as a function of conditions, as described in Chapter 2.

End Point

Generally speaking, a lane change or attempted lane change ends when the vehicle “settles” in the new lane (or in the original lane for a passing maneuver). In terms of relevance to the decision point, this point is not as critical as the lane-change initiation point. Nevertheless, task completion time will be affected if the end point is not properly defined. Settling point appears to provide the best concept for end of lane change because it allows for lane overshoot, variable lane transition time, and incomplete lane-change attempts. Settling time can be defined in terms of motion relative to the lane boundaries. Namely, when the vehicle’s lateral velocity relative to the lane is below a threshold for a specified period of time, the lane change is complete. Generally speaking, end point can be determined by having the data reductionist watch the side camera video for the vehicle to “settle” in the lane. This is an informal but accurate method of determining end point.

Categorization and Rating

After each lane change was identified, the event was categorized in terms of maneuver type, success/magnitude, and direction. Each maneuver was also rated in terms of severity and urgency. These categorization variables were described in detail in the Dependent Variables subsection but are briefly repeated here. There were eleven maneuver types (e.g., slow lead vehicle, enter, exit/prep exit, etc.), four categories for lane change success/magnitude (single, passing, multiple, unsuccessful), two directions (right, left), seven levels of the severity rating scale (1 = unconflicted, 7 = physical contact) indicating the degree to which the vehicle in the destination lane was cut off, and four levels of the urgency rating scale (1 = not urgent, 4 = critical) indicating how soon the lane change was needed based upon TTC with the closest POV in the same lane. During this phase, the information for each maneuver was entered into an Excel spreadsheet and saved, as illustrated in Figure 3.14.

Ss#	Rte	Usl Veh	ExpVeh	Gndr	Tape#	Date	Start	End	Type	Succ/Mag	Dir	Sev	Urg
8	US	SedDrv	SUV	Male	803	2/5/01	36115	36267	Slow Lead	S	L	1	3

Figure 3.14. Example of a Row from an Excel Spreadsheet Representing a Lane Change for Use With the Data Integration and Analysis Program.

In-Depth Sample Analysis

In-depth analyses were conducted after the final sample of slow lead vehicle lane changes was selected. A lane change data reduction program was developed to perform these analyses. In order to form a data packet, this program combined data from the video, radar, and sensor systems, as well as data entered into the Excel spreadsheet. The user manual for this program was developed to aid analysts in this effort (Appendix F), and it included a specific lane change event (#16) as an example that all analysts used as a model. Training for in-depth sample analysis generally followed the same procedure that was originally used for the identification and categorization process. Since each event was previously identified, the process of in-depth analysis was essentially a reliability check of the previously identified events. In rare cases, events were recategorized, or the start or end of the event was modified upon further review.

As an overview of the in-depth analysis, the maneuver start point was entered into the event data form, and the program automatically identified the point 10-seconds prior to the start point (t minus 10). The end point was also entered. Categorization data (i.e., maneuver type, direction, severity, and urgency) for each maneuver were then entered using a series of pull-down menus. Lane curve and transition data were also entered. Eye glance behavior was then analyzed starting from three-seconds before the lane change to the initiation of the lane change (during latency). Next, target data for each vehicle were retrieved for radar targets of interest. A complete archive of the event was then created. The result was a single integrated data file that could be used for review and statistical analysis. Finally, the original video segment was captured in a digitized format to be used in conjunction with the integrated data file. This digitized clip started at t minus 10 seconds and ended with the end point of the lane change (or attempted lane change). Approximately two seconds on each side of the above interval were also included. After events were identified, categorized, rated, and entered into the program, data packets were then available for statistical analyses.

Identifying Events

For a particular maneuver of interest (either a lane change event or a baseline event), the appropriate videotape and data file were located. The video file originally was used to identify maneuvers. Later, the video file was used to specify vehicles that were identified by the radar data and to determine eye glance patterns. The radar data file allowed the program to calculate range, range-rate, and time-to-collision (TTC) and to display a graphical representation of the maneuver. The event data form (Figure 3.15) was the first form to be encountered. Here, the raw file was loaded, and identification information was entered, including videotape identification, maneuver type, severity, urgency, and start and end synch values. Synch values were in units of tenths of a second. These values were superimposed on the video and were used as the time reference in the spreadsheet data. Thus, videotape segments could be correctly “registered” with sensor data. Participant information (ID number, run, age, gender, experimental vehicle, usual vehicle, road type [route], date, time, and event number) was automatically assigned by the program based on the raw data file.

The screenshot shows the 'Event Data Form' window with the following data:

Raw Data File:	C:\Lane_change_files\LaneData\RawData\	Browse
Video Tape ID:	S0803 SUV 460 Male SedDrv 020501	
Motivation:	Slow lead vehicle	
Severity:	1 - POV in Fast Approach Zone, Tr > 5s	
Urgency:	3 - Forced, TTC <= 3.0s	
Notes:	Single slow lead LC from right to left. Slow lead is POV1 (white SUV) in right lane. POV2 is vehicle far behind in left lane.	
Subject Number:	8	Event Number: 444
Run Number:	8	Sync 10 sec prior: 36115
Age:	26	Begin Sync Number: 36215
Gender:	Male	End Sync Number: 36267
Vehicle:	SUV	Sync Duration: 52
Usual Vehicle:	Sedan	Lane Data: Finished
Road Type:	460	Lane Curve: Finished
Date:	2-5-2001	Glance Data: Finished
Clock Time:	11:42:17	Target Data: Finished
OK		Save
Edit		Cancel

Figure 3.15. Event Data Form.

The lane curve history form (Figure 3.16) allowed the analyst to enter waypoints to estimate the edge-lines and curvature of the roadway, based on the video image. Parameters included curvature, offset, angle, and tilt. The curvature values are in feet, with positive values indicating curvature to the right and negative values indicating curvature to the left; a curvature that is infinite is actually a straight road. Offset is a measure in inches, with zero indicating the vehicle is centered within the lane and positive values indicating that the vehicle is to the right of center. The angle value represents the angle in degrees (yaw) of the centerline of the camera with respect to the centerline of the road horizontally, with positive values indicating that the vehicle is pointed toward the right and negative angles indicating that the vehicle is pointed to the left. However, an angle of zero degrees does not necessarily mean that the driver drove straight in the lane; it indicates that the camera is looking straight down the lane. Tilt (pitch) is also in degrees and is the vertical angle of the camera with respect to the road.

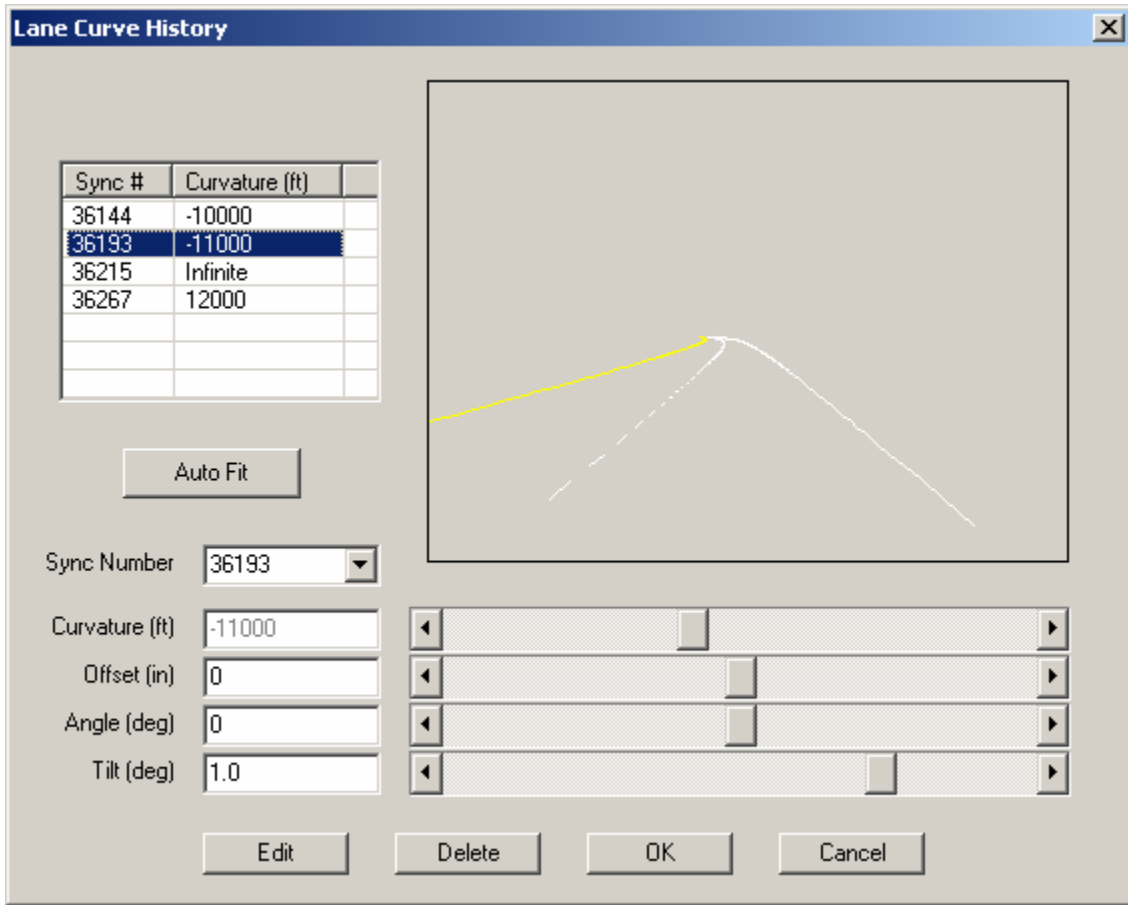


Figure 3.16. Lane Curve History.

Each parameter could be set using the appropriate scroll bar to approximate the lane edge-lines seen on the videotape. The primary use of this form was to facilitate a graphical display of the event and to assist in target identification. In most cases, the parameters offset, angle and tilt were not manipulated; curvature was the only parameter manipulated to line up the lane curve history window with the video image. Curvature data were not analyzed as part of the data analysis effort.

The lane transition history form (Figure 3.17) allowed the analyst to describe the event over time in terms of lane-changing milestones. Key elements included the number of lanes, original and destination lane, leave (begin) synch number, inside lane synch (point at which the inside of the vehicle crossed the lane line), outside lane synch (point at which the outside of the vehicle crossed the lane line), and settled (end) synch number. This information also helped the program to display the event accurately for event identification.

Lane Transition History [X]

Lane	To	Leave Sync	Inside Lane	Outside Lane	Settled Sync
2	1	36215	36226	36238	36267

Number of Lanes:

Begin Lane:

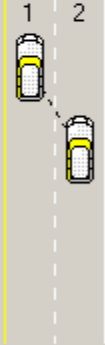
End Lane:

Leave Sync:

Inside Lane Sync:

Outside Lane Sync:

Settled Sync:



1 2

Edit Delete OK Cancel

Figure 3.17. Lane Transition History.

The eye glance form (Figure 3.18) allowed the analyst to perform an eye glance analysis in which specific eye behavior data associated with a particular maneuver were entered. The glance direction (location) and beginning and ending synch number were entered and duration was calculated automatically. The glance data form was used in conjunction with the video data to identify where the driver was looking during the maneuver.

Glance	Direction	Begin Sync	End Sync	Duration (s)
7	Rear View Mirror	36201	36208	0.8
8	Center Forward	36209	36213	0.5
9	Rear View Mirror	36214	36217	0.4
10	Center Forward	36218	36221	0.4
11	Left Blind Spot	36222	36226	0.5
12	Right Forward	36227	36237	1.1

Glance Direction: Begin Sync: End Sync:

Buttons: Edit, Delete, OK, Cancel, VCR

Figure 3.18. Eye Glance Form.

The radar distance screen (Figure 3.19) displayed radar data in a graphical format. The abscissa was the time synch (1/10 second) value and the ordinate was range (feet). The radar target identification numbers were also displayed (e.g., 28, 29). Each of three views (front radar, rear driver radar, and rear passenger radar) could be displayed via toggle buttons. A vertical line along the abscissa indicated the time location as the event progressed.

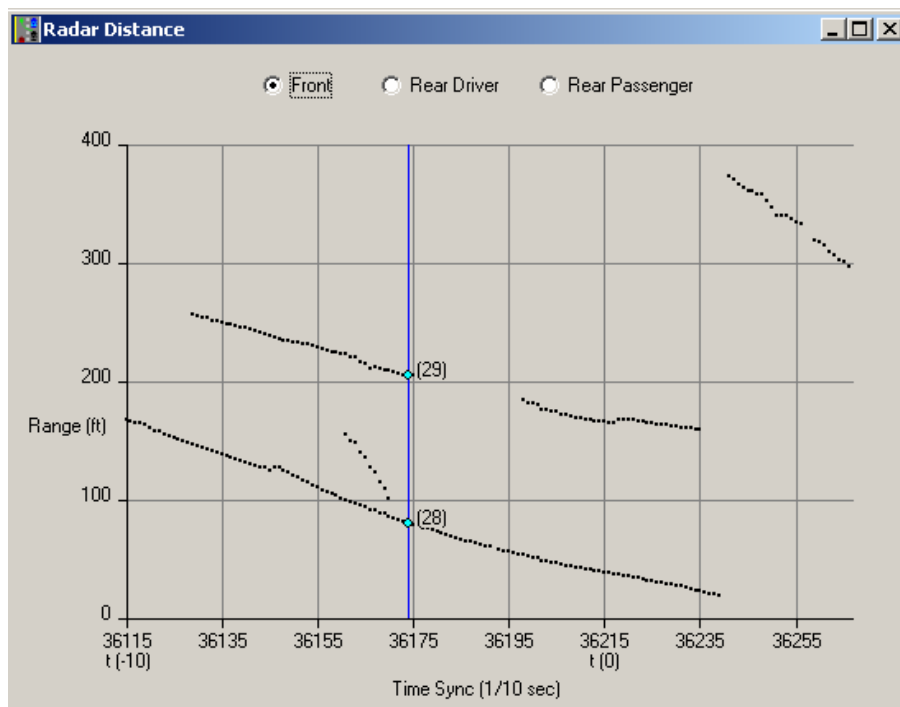


Figure 3.19. Radar Distance Screen (Front Radar).

The target identification form (Figure 3.20) allowed the analyst to identify each target with a unique identification number. Key elements of the target identification form included target number, description, radar, radar identification, and begin and end synch numbers. The target number is the re-assigned number associated with a particular target. In general, Target 1 was the closest POV, Target 2 was the next closest POV, and so on. The description box included a brief description of the POV, including color of the vehicle (dark or light, since the video was black and white), position, and action. Radar (front, rear driver [left], or rear passenger [right]) referred to the radar unit that detected the target of interest. Radar identification referred to the original ID number (e.g., Target #28) assigned to a particular target by the radar unit.

After all of the targets for a particular vehicle were identified, a unique target number was then assigned by the program (Target 1, Target 2, and so on). For the event shown in Figure 3.20, Target 1 was associated with radar target 28 from the front radar.

Radar	Radar ID	Begin Sync	End Sync
Front	28	36115	36191
Front	28	36193	36239

Figure 3.20. Target Identification Form.

Note that the same radar target could have multiple ID numbers because the radar system would acquire, lose, and then reacquire the same target due to masking by other vehicles or the target going out of range. In addition, if a radar target was acquired by one sensor and then another, each radar system would assign independent target numbers. The begin and end synch numbers represented the beginning and ending of the lane change event. These corresponded to the synch numbers present on the video as well as the sensor data file.

The radar display form was a graphical, “bird’s eye view” of all radar targets as they appeared during an event (Figure 3.21), corresponding to the radar distance screen (Figure 3.19). A unique vehicle icon (SUV or Sedan) was displayed with radar convergence regions displayed

as appropriate (i.e., front, rear driver, rear passenger). Figures 3.22 illustrates the lane change program windows and 3.23 illustrate a video file. Finally, Figure 3.24 illustrates how one might view the lane change program while watching a video file.

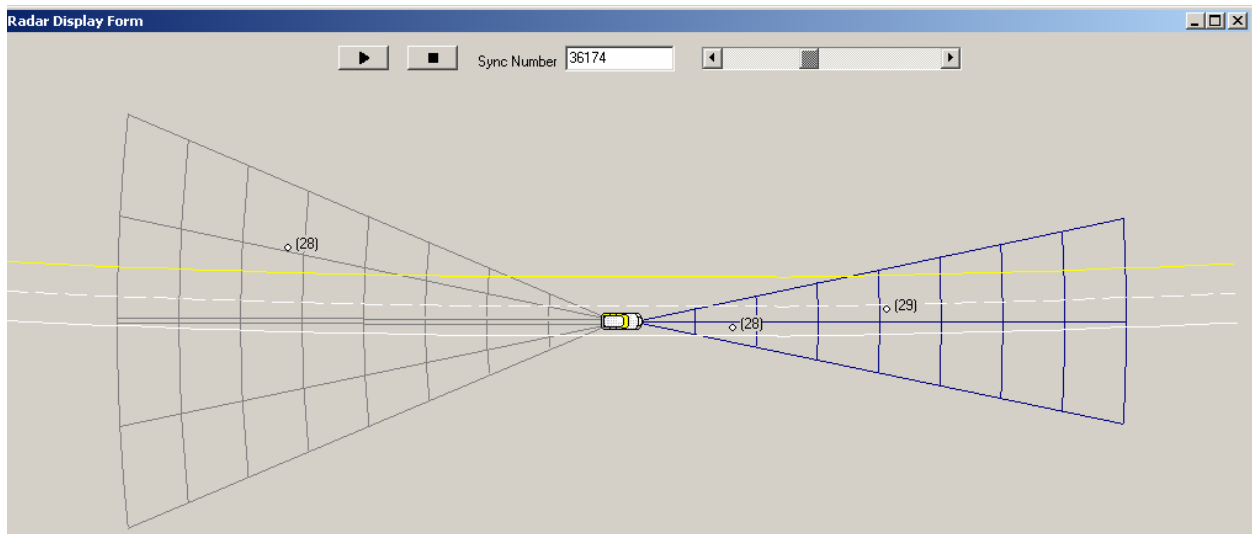


Figure 3.21. Radar Display Form.

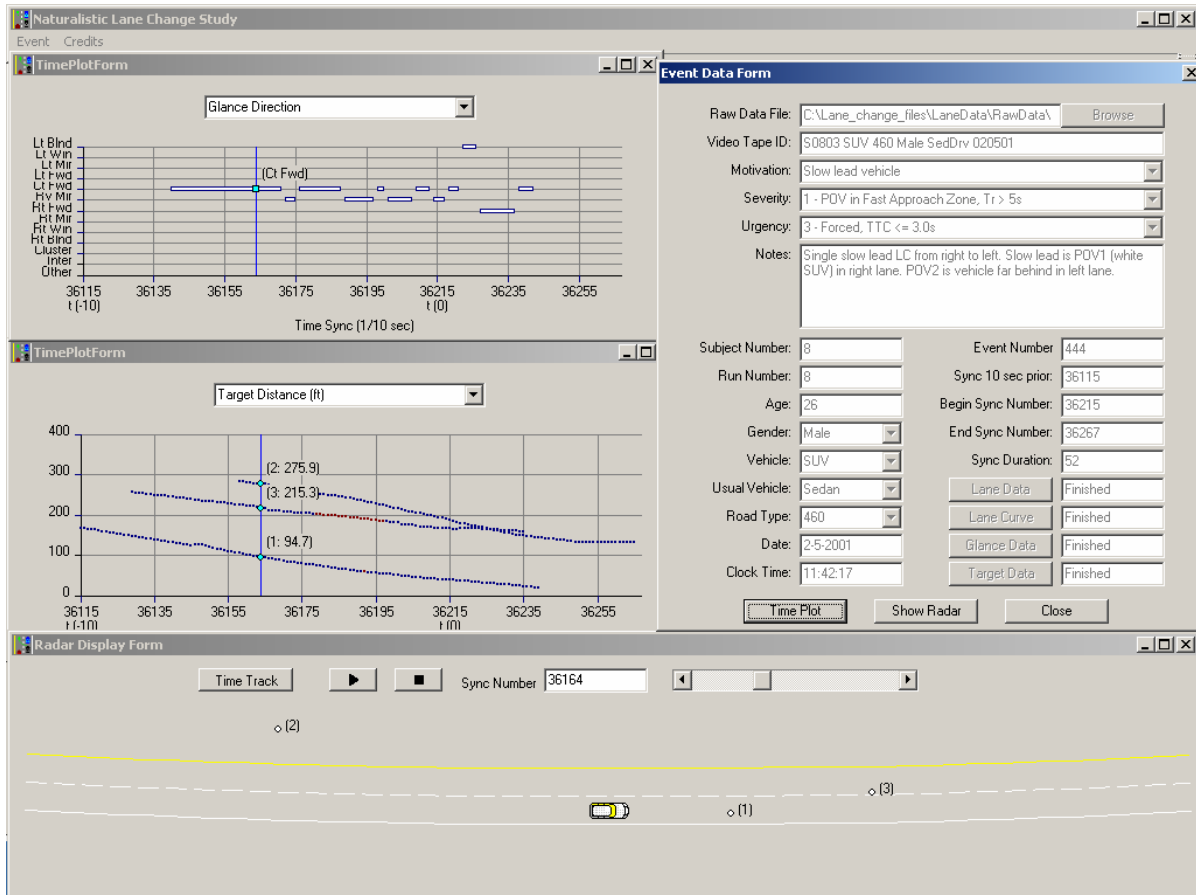


Figure 3.22. Sample of Lane Change Analysis Program Windows at t_0 Showing Target Distance, Eye Glance Position, Radar Display, and Event Data.



Figure 3.23. Video Image Corresponding to t_0 in Lane Change Analysis Program Windows.

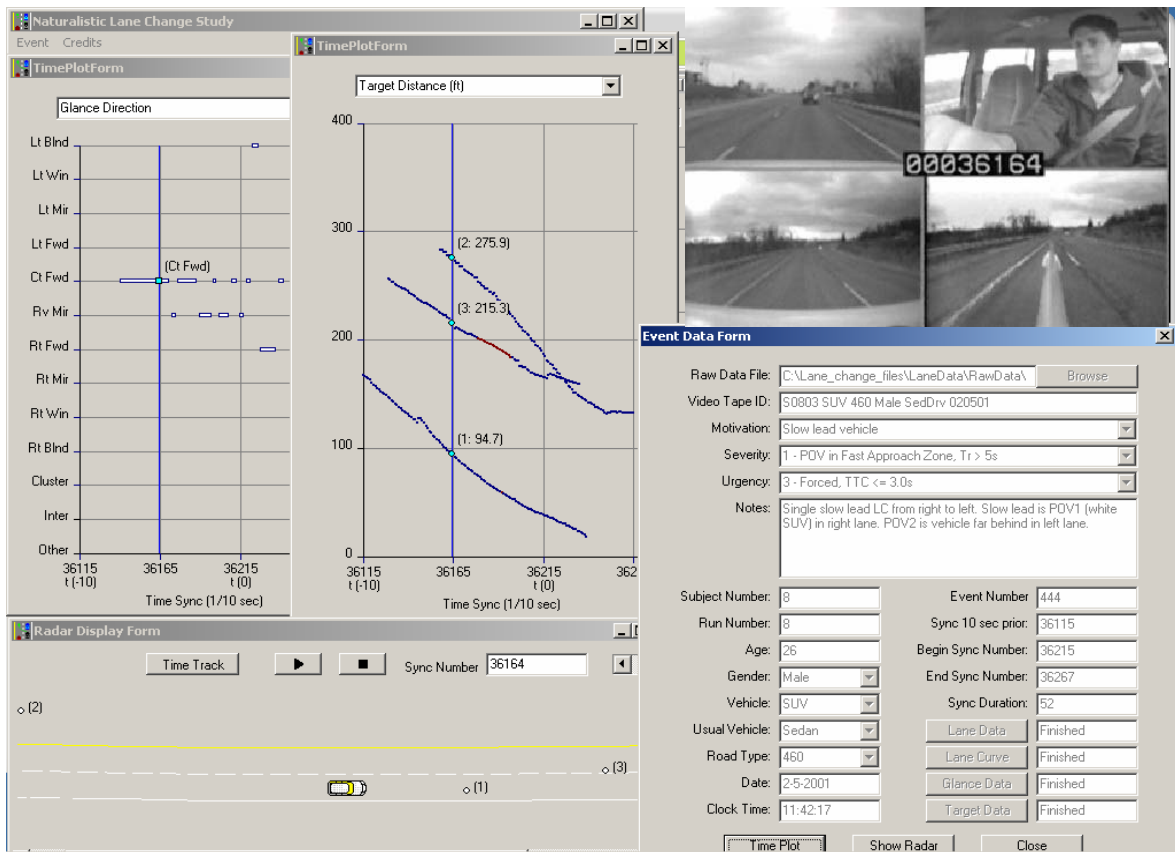


Figure 3.24. Lane Change Analysis Program with Video Image.
 (click figure to play demo file or select from below)

- [demo_small.mov](#) (1.96 MB)
- [demo_med.mov](#) (6.72 MB)
- [demo_large.mov](#) (7.83 MB)
- [demo_mpeg.mpg](#) (3.85 MB)

In-Depth Sample and Baseline Selection

This section describes sampling that was used for data analysis and event selection. The total available data included 8,667 lane changes. Of this total, 3,227 were slow lead vehicle lane changes. Over 90% of these maneuvers were rated with low severity and urgency ratings, with the remaining 10% being rated as more severe or urgent (e.g., ≥ 2 in severity or urgency). Comparisons were made among three levels of conflict severity across all levels of urgency as illustrated by Table 3.7. The separation into the three levels of was done simply for convenience of discussion. Severity indicated the presence of a vehicle in the adjacent lane. As a reminder, a severity rating of “5” indicates that a vehicle was present in the PZ. A rating between 2 and 4 indicates that a vehicle was present in the FAZ. A severity rating of 1 indicates that either a vehicle was present within the adjacent destination lane or there was no vehicle present at all at the time of the lane change initiation (t_0).

Table 3.7: Distribution of Slow Lead Vehicle Lane Changes by Severity.

FREQUENCY		
Slow Lead Veh	Total	%
Severity = 5	176	5.5
2 \geq Severity \geq 4	59	1.8
Severity = 1	2,992	92.7
Total	3,227	100.0

Previous to this dissertation, the entire set of 8,667 lane changes was analyzed (Lee, Olsen, & Wierwille, 2003). This set of lane changes included 11 lane-change maneuver types (e.g., entering, exit/prepare to exit). A sample of 500 lane changes, of various maneuver types, was analyzed in-depth using the previously described lane change identification application to identify eye glance behavior and to categorize other relevant information, including turn signal timing, velocity, distance, and TTC. Sampling emphasized high severity and urgency ratings, included predominant maneuver types such as slow lead vehicle entering/exiting the roadway and returning to the original lane, and was carefully selected to emphasize lane changes in the more severe and urgent categories. The remainder of the sample consisted of lane changes of other less common maneuvers. In general, the sample was selected to provide a representative sample of the full data set in terms of maneuver type. Most of the lane changes in the sample (301/500 or 60%) were slow lead vehicle lane changes. For this dissertation, a subset of this sample of lane changes was selected from the set of 500 that were previously identified and analyzed.

A form of stratified sampling was conducted to select the final sample. This involves subdividing a heterogeneous population into groups (strata) and selecting samples from each of those groups (Mason, Gunst, & Hess, 1989). The purpose for selecting maneuvers from these groups was to allow the total sample to represent a variety of maneuvers. It is believed that selecting maneuvers in this manner best represents maneuvers from a range of drivers (e.g., across gender and usual vehicle). In addition, a range of driving conditions (routes and vehicles) over a wide number of days during a 10-month period are represented. Initially the strata were based upon three groups of severity ratings; within each group, lane changes were then grouped by urgency rating. A total of 120 maneuvers was selected and then further broken down into three groups (low, moderate, high severity ratings) of 40 maneuvers. A set of baseline events

(straight-ahead driving) (i.e., 32 maneuvers or 2 maneuvers for each of 16 participants, plus an additional 8 maneuvers) was also selected as discussed in the next section.

Of the population of 3,227 slow lead vehicle lane changes, 2,992 (93%) of these were rated low (i.e., severity rating of 1). Of these, the vast majority (i.e., 2,751) were rated low in urgency as well (i.e., these are the “1 and 1” cases, with severity = 1 and urgency = 1). Of the set of maneuvers rated low in severity, there were also cases in which the urgency was rated as moderate (2) or high (≥ 3). The number of cases in which severity = 1 and urgency = 2 was 232 cases (see the bottom of Figure 3.25). In a similar manner, there were only ten “1 and 3” cases, in which severity = 1 and urgency was ≥ 3 .

The distribution of all slow lead vehicle lane changes that take both severity and urgency into consideration is illustrated in Figure 3.25. As expected, the majority of maneuvers were rated at low urgency ratings. A sample of 40 maneuvers from each of four groups (3 severity groups and 1 baseline group) were analyzed in depth, for a total of 160 maneuvers. Note that one maneuver originally classified with a $2 \leq \text{severity} \leq 4$, was later re-classified as a severity = 5 event, so not exactly 40 events exist in each category of severity. The final sample of slow lead vehicles is illustrated in Figure 3.26, including 120 slow lead vehicle lane changes and 40 baseline events.

Straight-ahead segments were selected as a baseline that would be used to compare lane change events. In essence, this was treated as a crossover design in which participants acted as their own control. Performance measures were compared for straight-ahead segments and lane-change events. This approach seemed logical, as opposed to comparing performance across participants, and assumed that the driver was behaving as he or she normally would (i.e., he or she is not behaving in a manner that is outside of normal for that particular driver).

Baseline segments were selected in a quasi-random manner to represent all participants. A total of 120 lane change maneuvers were included; however, it is believed that baseline segments for a particular participant did not vary dramatically from segment to segment. For this reason, at least two segments were selected to represent each participant, for a total of 32 segments (2 x 16 participants). An additional eight segments were selected to represent participants who made frequent lane changes. For example, if participant # 2 accounted for a large percentage of the total lane changes observed, then one or two additional baseline segments for participant # 2 were included. For each participant, each baseline segment was evaluated both visually (i.e., by watching the videotape) and descriptively to evaluate if observed dependent measures were within reasonable limits (i.e., the driver was not performing an unusual maneuver).

Each baseline segment was 10 seconds in length. The purpose for selecting 10 seconds as the duration of the segment was because this was the approximate duration of a lane change (~6 seconds) plus three seconds before the lane changes starts. Ten seconds of data seemed a reasonable length for comparison purposes. Each baseline segment was selected from the videotape on which a maneuver occurred, at a point before the comparison lane change occurred. The segment was selected during a period in which no lane changes were occurring. Where possible, a baseline event was selected that was at least 60 seconds from any of the 8,667 lane change events. In this manner, a matched sampling technique was used to select baseline segments.

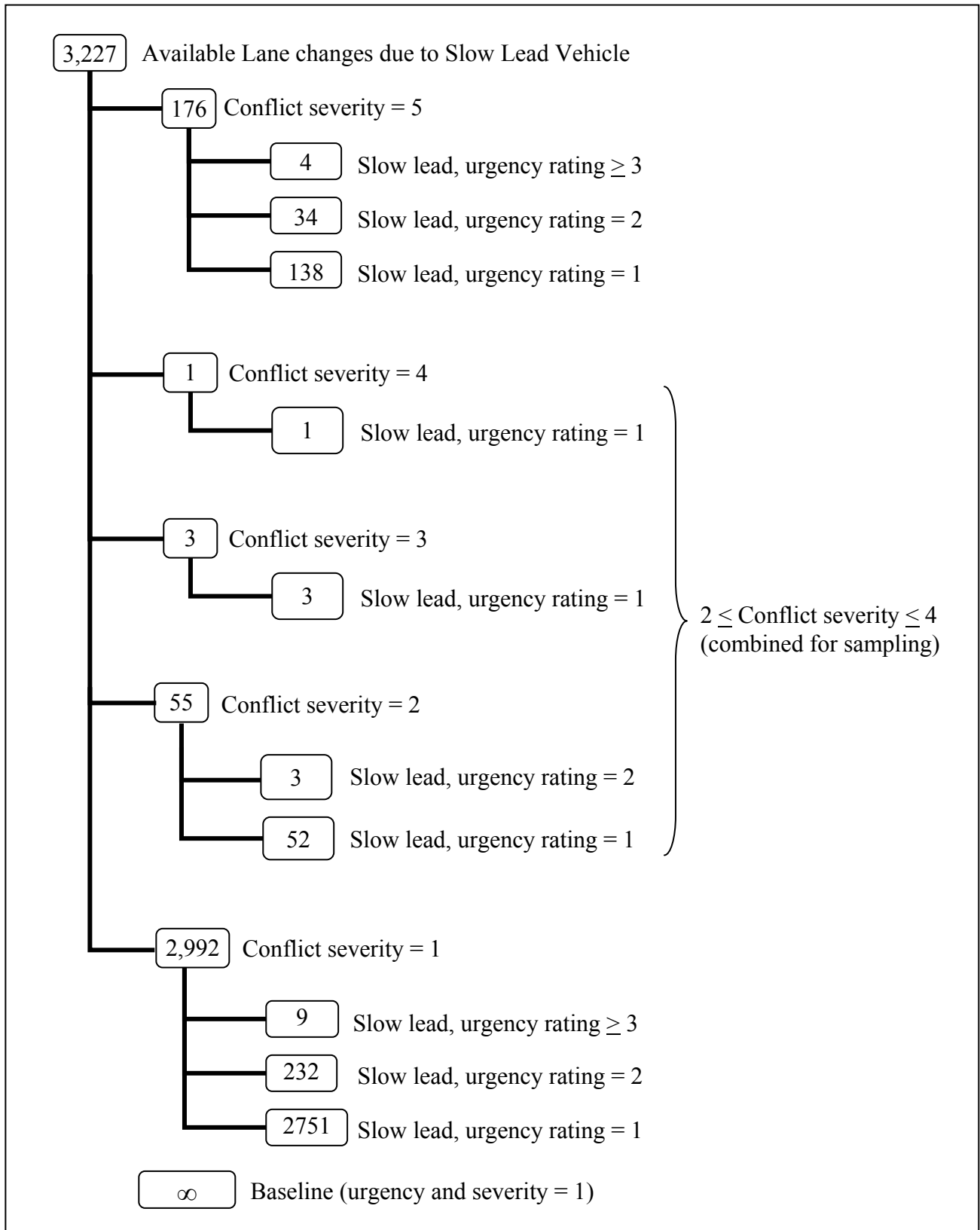


Figure 3.25. Available Data for Lane Changes with Slow Lead Vehicle Present.

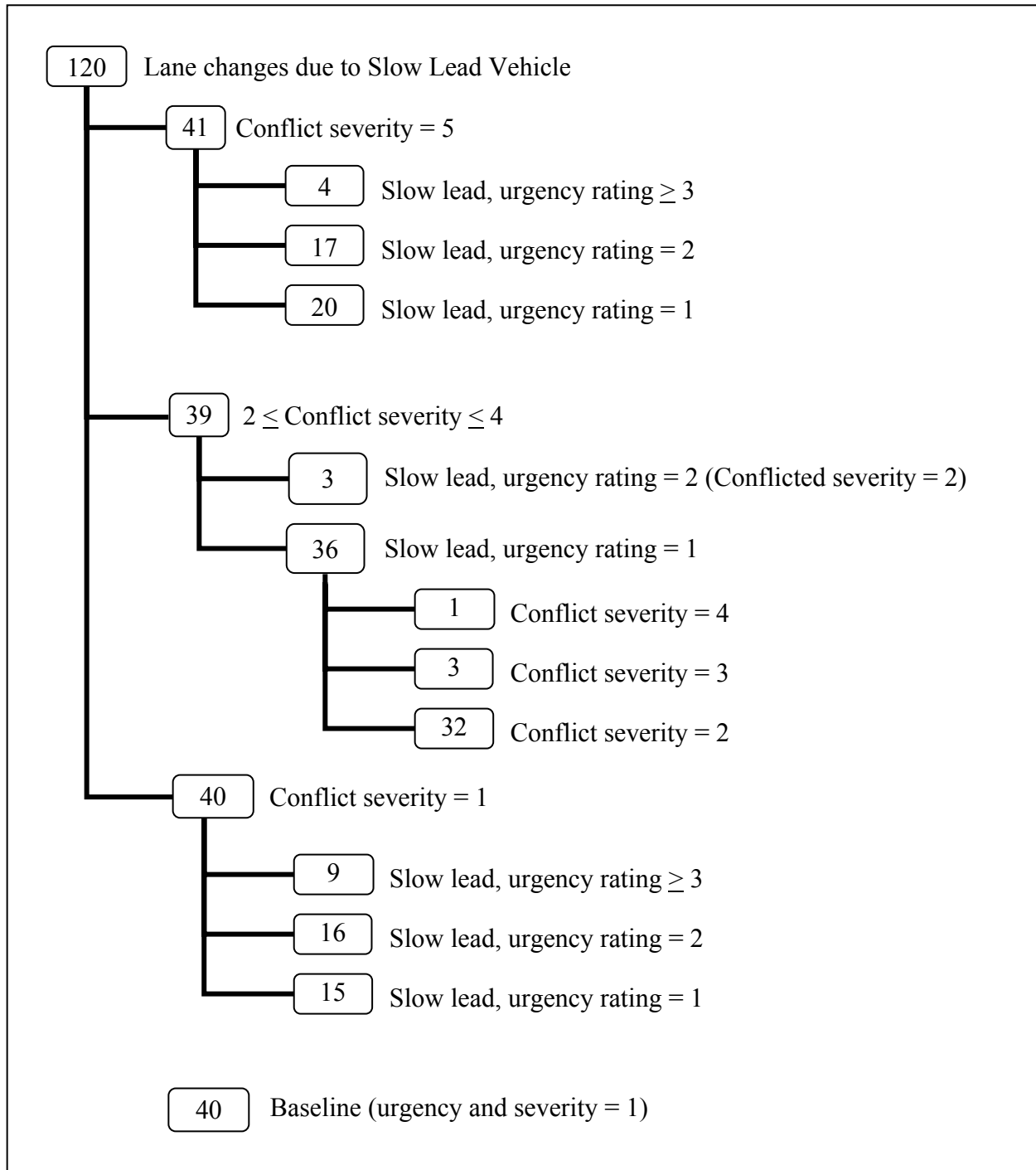


Figure 3.26. Sample of Lane Changes in Terms of Severity and Urgency.

A Note on Sampling

It is significant to discuss why sampling based on random sampling was not performed, such as simple or stratified random sampling. A simple random sample is a group of observations obtained from a population in such a manner that every group of items has an equal

chance of being selected as the sample (Mason, Gunst, & Hess, 1989). If simple random sampling had been used, such a sample would very likely contain lane changes from each of the 11 maneuver types. Selecting a simple random sample would also most likely result in a sample consisting of maneuvers rated low in both severity and urgency, since ratings with low ratings were very common. For this dissertation, however, since only slow lead vehicle lane changes were of interest, the final sample was constrained to this type of maneuver. In addition, sampling was desired that emphasized lane changes in the more severe and urgent categories. Finally, a sample was desired that represented all participants where possible.

As mentioned, stratified sampling was used for selecting the lane changes for analysis. True stratified random sampling involves the selection of simple random samples from each group of strata (Mason, Gunst, & Hess, 1989). However, this was not desired, for the same reasons that simple random sampling was not used. A sort of matched and stratified sampling was conducted in that, for each level of severity, samples were selected so that each participant was represented in the sample where possible. Samples were selected from groups (e.g., in terms of urgency, severity, participant) but not in a random manner.

CHAPTER 4: ANALYSIS AND RESULTS

Detailed analyses were conducted on the entire set of 3,227 slow lead vehicle lane changes. A brief sub-section first explains the differences between primary and secondary data analysis, as well as the rationale for using secondary data analysis in this dissertation.

Primary and Secondary Data Analysis

In primary data analysis the individual who collected the data also performed the analysis (Church, 2001). Typically, a specific problem is identified, a hypothesis is created, an experiment designed, data are collected, and analyses are performed. Secondary data analysis involves the use of existing data (e.g., archives) that are collected for purposes similar to a prior study. The data is then used to pursue a research interest that is distinct from that of the original work (i.e., a new research question or an alternative perspective on the original question) (Heaton, 2002; Hinds, Vogel, & Clarke-Steffen, 1997; Szabo & Strang, 1997). According to Graves (1998), secondary data analysis is the analysis of data that either 1) was not collected by the analyst or 2) was collected for a different problem from the one currently under analysis.

This dissertation used existing data collected for a prior study to pursue an alternative perspective on an original question. For the original lane change data collection effort, data were collected in a general manner to support exploratory investigation and categorization of a variety of lane change types (e.g., entering, exiting) (Lee, Olsen, & Wierwille, 2003). The experimenter was responsible for primary data collection; however, the specific focus of this dissertation research was not identified until after data collection began.

Specifically, the purpose of this effort was threefold: 1) to characterize normal lane changes in which a slow lead vehicle was present, 2) to develop predictive models distinguishing baseline (straight-ahead) driving from lane changing (i.e., develop predictive logistic regression models), and 3) to provide engineering design guidelines for lane change collision warnings and for the design and function of crash avoidance systems.

This effort does not suffer many of the problems associated with some secondary analyses. For example, secondary analyses are often performed by researchers not involved in the primary data collection effort. This can be problematic when secondary analyses are desired because the researcher may be unfamiliar with the data format, the method of data collection, the coding structure, or other details of the original data collection effort. That was not true in this case since the experimenter was involved in the initial data collection, assisted in event identification, and was involved in the data archival process. One potential problem with this dissertation, however, is that the experimenter was overly familiar with these data--one might argue that the experimenter could be biased when performing further research. However, data were recorded automatically without experimenter intervention. Data were then reviewed by a team of four analysts, including the experimenter. All events were identified, categorized, and rated by the team using operational definitions for data identification, categorization, and rating, which were created so that this process would be uniform. The sample of data to be analyzed was selected by the experimenter with, in some cases, the guidance of senior team members.

The fact that a new set of research questions (as compared to the original study) has been proposed with a focus on slow lead vehicle lane changes could be viewed as a limitation. For example, it was not clearly known that slow lead vehicle lane changes would be so prevalent (> 37%) before the study was conducted. During data collection and in preparation for this dissertation, the experimenter discovered a need to further investigate slow lead vehicle lane changes. Fortunately, data were collected in a generalizable manner (i.e., participants did not

know the specific purpose of the experiment) and the operational definitions used for the original study could be used for the secondary analysis with no modifications (e.g., the start and end point definitions were still useful).

In terms of validity, there were likely some limitations present as a result of conducting secondary data analysis. As previously mentioned, the fact that the experimenter was involved in both the data collection and the analysis may be a source of bias. Limitations also exist in terms of ecological validity (i.e., whether or not one can generalize from observed behavior in the laboratory to natural behavior in the world); however, since drivers had some minimal constraints imposed upon them (e.g., driving alone, without sunglasses, only during work days), these limitations exist for *all* observations made in the original study. The ramification of these limitations will be acknowledged in the discussion section of this document, as warranted. Although the experimenter was somewhat familiar with these data, with a total of 8,667 events, it was essentially impossible for anyone to become extremely familiar with the data and introduce bias.

All Slow Lead Vehicle Lane Changes

Analysis included one-way and two-way distributions of lane changes as a function of severity ratings, urgency ratings, and lane change duration for the full set of 3,227 slow lead vehicle lane changes; this is to be referred to as the “large set.” There were four independent variables in the experimental design: route (interstate or US highway), usual vehicle (whether the participant normally drove a sedan or SUV), gender (male or female), and experimental vehicle (instrumented sedan or SUV). One-way and two-way analyses of variance (ANOVA) and chi-square goodness-of-fit analyses were performed.

Main Effects

The ANOVA was performed to investigate variable interactions (i.e., route, usual vehicle, gender, and experimental vehicle) for the dependent measures (quantitative data) of duration, urgency, and severity. One-way and two-way distributions of lane changes are presented as a function of the independent variables. Chi-square analyses were also performed to detect differences in actual and expected values for the frequency counts (categorical data). In this way, behavior differences among independent variables were evaluated in terms of each of the dependent variables.

ANOVA Results. For the total set of slow lead vehicle lane changes, duration was analyzed only for the *single* lane changes. Of the large set ($N = 3,227$), there were 2,168 single lane changes. Results for the general linear model (GLM) procedure revealed that there were no significant main effects or interactions for duration. Overall, single lane changes had a mean duration of 6.26 s ($SD = 2.27$).

For urgency and severity, the entire large set of 3,227 lane changes was analyzed. Route was significant for urgency, $F(1, 31) = 5.24, p = 0.05$. For interstate lane changes, the mean urgency was 1.05 ($SD = 0.21$), and for highway lane changes, the mean urgency was 1.14 ($SD = 0.37$), as illustrated by Figure 4.1. As a reminder, urgency is related to the TTC with the slow lead vehicle ahead. There were no other significant findings for urgency or severity.

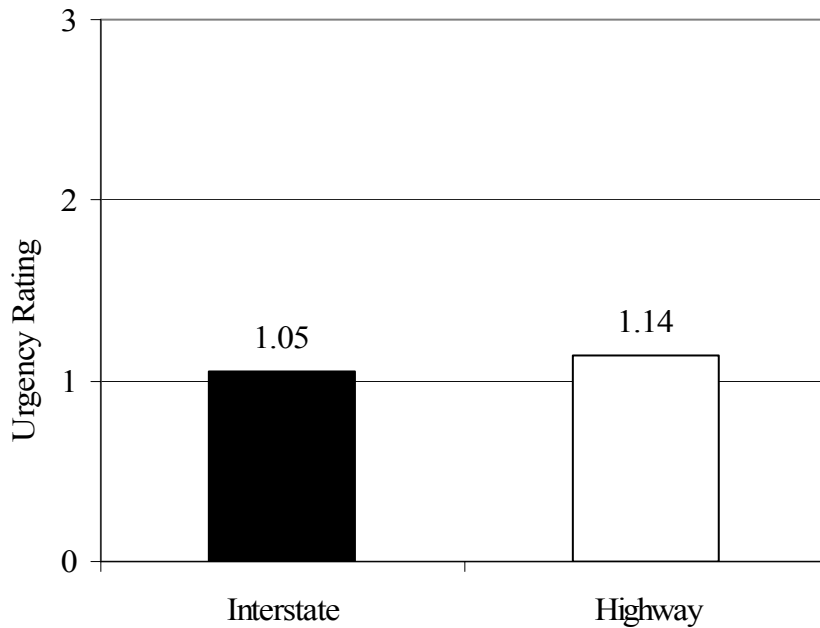


Figure 4.1. Mean Urgency Ratings for Route.

Chi-square Results. For the chi-square analysis of frequency, route was significant. Interstate drivers completed 1,699 lane changes, while highway drivers completed 1,528 lane changes, $\chi^2(1) = 9.0614$, $p = 0.003$. However, an examination of the normalized data indicated that *interstate drivers actually performed significantly fewer* slow lead vehicle lane changes per mile than highway drivers, $t(30) = 2.83$, $p = 0.008$. Interstate drivers performed 0.11 lane change/mile (1,699 slow lead vehicle lane changes over 16,345 miles), while US highway drivers performed 0.17 lane change/mile (1,528 slow lead vehicle lane changes over only 8,851 miles), as illustrated by Figure 4.2. The normalized data analysis indicates that most of the difference in frequency was due to the number of lane changes performed on the two routes.

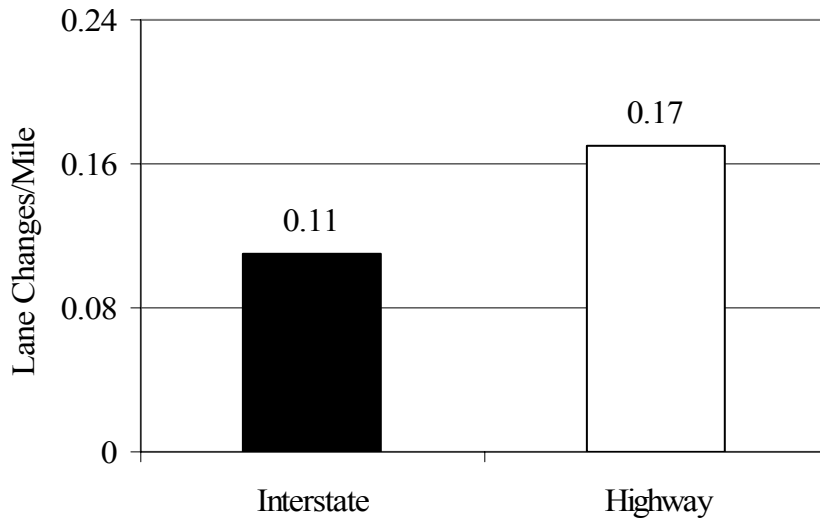


Figure 4.2. Mean Lane Change Rate Per Mile for Route.

For usual vehicle, SUV drivers completed 1,330 lane changes (41.2%) and sedan drivers completed 1,897 lane changes (58.8%), $\chi^2(1) = 99.6247, p < 0.0001$, as illustrated by Figure 4.3. An examination of the normalized data also indicated that SUV drivers performed fewer slow lead vehicle lane changes per mile (0.11) than sedan drivers (0.16), which follows the same pattern as the frequency counts, which was also significant, $t(30) = -2.44, p = 0.02$.

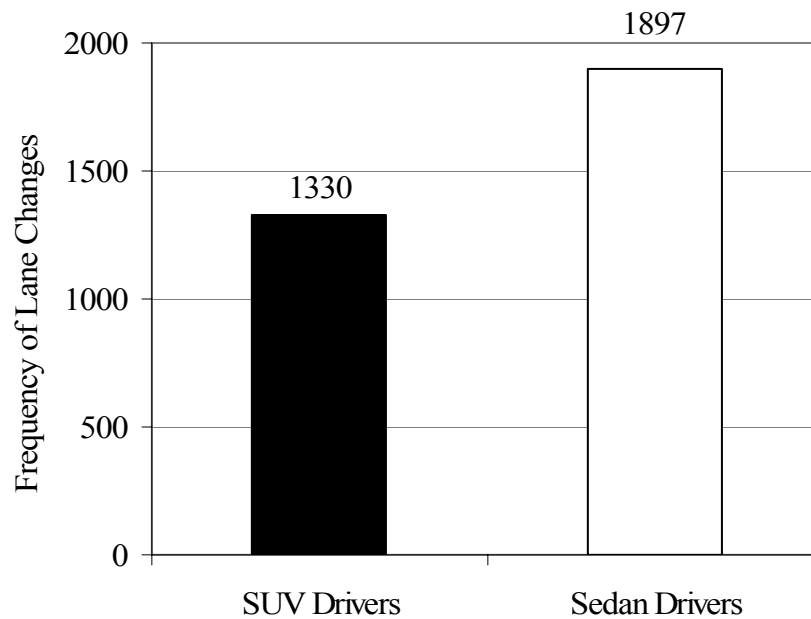


Figure 4.3. Frequency of Lane Changes for Usual Vehicle (Vehicle Normally Driven).

The gender main effect was also significant; males completed 1,699 lane changes (52.6%), while females completed 1,528 lane changes (47.4%), $\chi^2(1) = 9.0614, p = 0.003$, as illustrated by Figure 4.4. An examination of the normalized data for gender also indicated that females performed fewer slow lead vehicle lane changes per mile (0.13) than did males (0.14); however, this difference was not significantly different, as compared to the frequency counts. Table 4.1 summarizes these findings, including the frequency, duration, urgency, and severity, as well as the number of miles and lane changes per mile for each of these independent variables. Appendix G shows the SAS code and full results for the ANOVA and chi-square analyses.

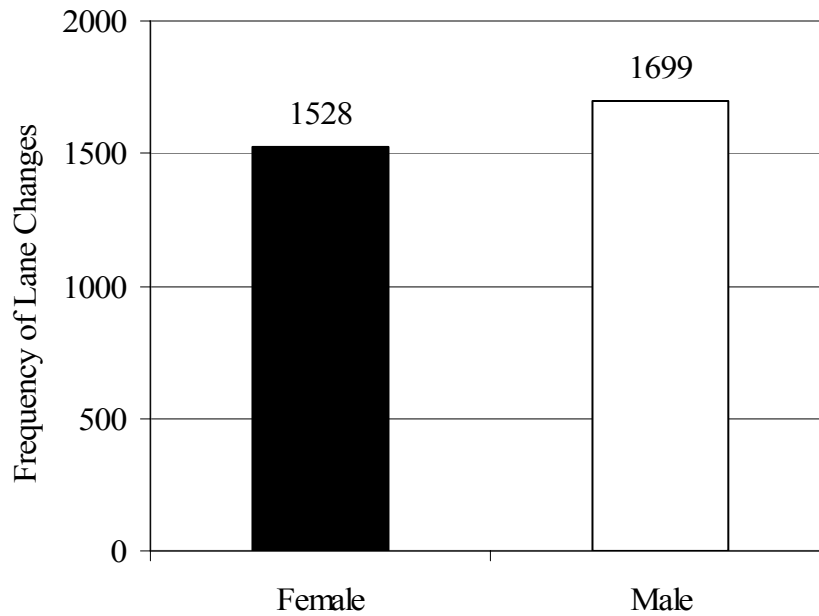


Figure 4.4. Frequency of Lane Changes for Gender.

Table 4.1: Means (and standard deviations) Distributions for Route, Usual Vehicle, Gender, and Experimental Vehicle for Slow Lead Vehicle Lane Changes, Frequency, Miles, and Lane Changes per Mile.

Independent Variable	Level	Mean Duration * (Seconds) (StDev)	Mean Urgency (1-4) (StDev)	Mean Severity (1-7) (StDev)	Lane Change Frequency	Miles Driven	Lane Changes Per Mile
Route	Interstate	6.18 (1.65)	1.05 (0.21)	1.33 (1.07)	1,699	16,345	0.11
	Highway	6.39 (3.06)	1.14 (0.37)	1.13 (0.70)	1,528	8,851	0.17
Usual Vehicle	SUV Drv	6.43 (2.15)	1.07 (0.25)	1.18 (0.78)	1,330	11,988	0.11
	Sed Drv	6.13 (2.35)	1.11 (0.33)	1.28 (1.00)	1,898	11,960	0.16
Gender	Male	6.08 (2.32)	1.12 (0.35)	1.28 (0.98)	1,699	11,886	0.14
	Female	6.45 (2.20)	1.06 (0.24)	1.19 (0.83)	1,528	12,063	0.13
Experimental Vehicle	SUV	6.22 (2.60)	1.09 (0.31)	1.25 (0.93)	1,584	11,483	0.14
	Sedan	6.30 (1.90)	1.09 (0.30)	1.23 (0.90)	1,643	12,467	0.13
TOTAL	ALL	6.26 (2.27)	1.09 (0.30)	1.24 (0.92)	3,227	23,949	0.13

*Mean Duration analysis were only conducted for *single* lane changes.

Gray and Bold Italics = significant main effect of $p \leq 0.001$. Gray = significant main effect of $p \leq 0.05$.

Frequency Differences. Table 4.2 contains the participant-by-participant descriptive statistics for normalized frequency. (Note: participants are numbered 2 through 17; participant 1 did not complete the experiment). The extreme values are 0.04 and 0.29 lane changes/mile. Figure 4.5 is a histogram of slow lead vehicle lane changes per mile, showing the relatively tight clustering of this parameter. Note that slow lead vehicle lane changes account for only a portion of all types of lane changes that were performed while driving (e.g., lane changes to exit). When looking at all eleven lane change types, drivers completed an average of 0.36 lane change/mile (Lee, Olsen, & Wierwille, 2003). Since slow lead vehicle lane changes accounted for 37.2% of all lane changes observed, one would expect the number of lane changes/per mile to be lower as compared to larger set of 8,667 lane changes. That is, since analysis was conducted only for slow lead vehicle lane changes, the average lane change/mile rates were lower because slow lead vehicle lane changes were a subset of the set of all lane change types observed. In fact, for the set of slow lead vehicle lane changes, drivers completed an average of 0.13 lane change/mile.

Table 4.2: Slow Lead Lane Changes per Mile for Each Participant by Experimental Vehicle Driven.

Part#	Route	Driv. Type	Gender	Exp Veh	Dur	Urg	Sev	LCs	Miles	LC/Mile
2	I	SedDrv	M	SUV	5.50	1.08	1.12	164	1016.3	0.16
2	I	SedDrv	M	Sed	6.04	1.03	1.41	121	1190.3	0.10
3	I	SedDrv	F	SUV	6.02	1.00	1.15	117	920.1	0.13
3	I	SedDrv	F	Sed	5.94	1.05	1.03	148	1247.1*	0.12
4	US	SedDrv	F	SUV	6.51	1.04	1.00	53	427.8	0.12
4	US	SedDrv	F	Sed	6.48	1.05	1.00	56	448.4	0.12
5	US	SedDrv	M	SUV	5.63	1.18	1.27	161	688.4	0.23
5	US	SedDrv	M	Sed	5.68	1.14	1.23	189	662.0	0.29
6	I	SUVDrv	F	SUV	6.87	1.01	1.07	68	950.6	0.07
6	I	SUVDrv	F	Sed	6.92	1.02	1.21	56	1258.5†	0.04
7	I	SUVDrv	M	SUV	5.91	1.02	1.33	60	973.4	0.06
7	I	SUVDrv	M	Sed	6.41	1.02	1.08	63	848.4	0.07
8	US	SedDrv	M	SUV	6.58	1.35	1.29	95	455.6	0.21
8	US	SedDrv	M	Sed	6.02	1.35	1.25	113	455.3	0.25
9	I	SedDrv	M	SUV	6.12	1.04	2.01	82	634.9	0.13
9	I	SedDrv	M	Sed	5.99	1.07	1.23	60	700.0	0.09
10	US	SUVDrv	M	SUV	6.32	1.15	1.08	150	607.9	0.25
10	US	SUVDrv	M	Sed	6.28	1.08	1.06	127	672.7	0.19
11	US	SUVDrv	F	SUV	7.23	1.02	1.12	83	447.6	0.19
11	US	SUVDrv	F	Sed	7.57	1.04	1.06	72	509.2	0.14
12	I	SedDrv	F	SUV	6.67	1.05	1.62	137	927.4	0.15
12	I	SedDrv	F	Sed	6.69	1.05	1.69	166	897.7	0.18
13	US	SUVDrv	F	SUV	6.08	1.00	1.06	17	307.1	0.06
13	US	SUVDrv	F	Sed	5.86	1.18	1.14	28	306.6	0.09
14	US	SUVDrv	M	SUV	6.68	1.06	1.16	63	772.2	0.08
14	US	SUVDrv	M	Sed	7.40	1.07	1.09	85	800.8	0.11
15	I	SUVDrv	M	SUV	6.30	1.08	1.53	91	704.5	0.13
15	I	SUVDrv	M	Sed	6.05	1.09	1.68	76	703.3	0.11
16	I	SUVDrv	F	SUV	6.03	1.06	1.06	127	1019.7	0.12
16	I	SUVDrv	F	Sed	6.14	1.05	1.17	164	1105.9	0.15
17	US	SedDrv	F	SUV	5.50	1.15	1.00	117	629.0	0.19
17	US	SedDrv	F	Sed	6.04	1.11	1.03	119	660.4	0.18
ALL Slow Lead Lane Changes					6.26	1.09	1.24	3,227	23,949.1	0.13

* Participant drove 3 extra days (6 commutes) for testing purposes

† Participant drove 2 extra days (4 commutes) for testing purposes

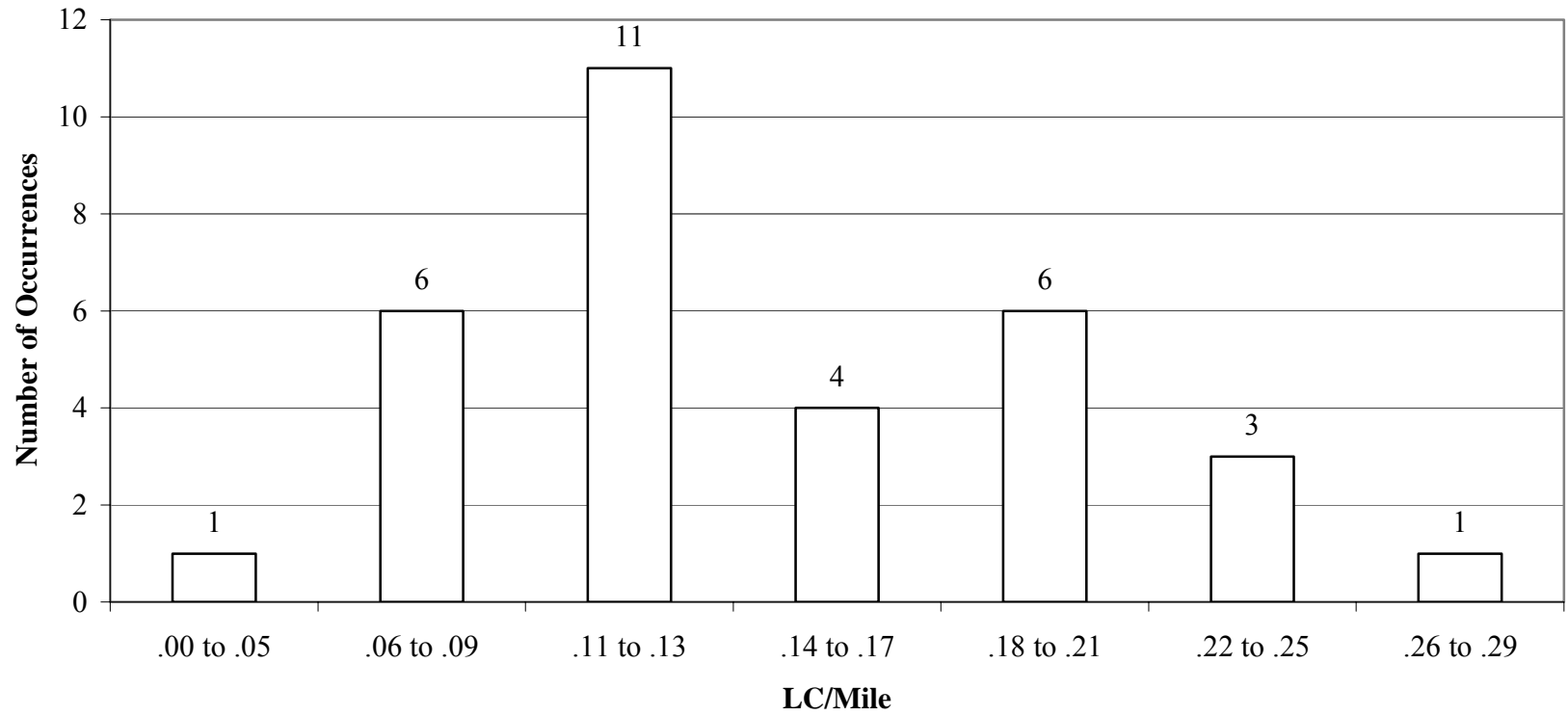


Figure 4.5. Histogram of Average Number of Slow Lead Vehicle Lane Changes per Mile.

Interaction Effects

ANOVA Results. Next, interactions among route, usual vehicle, gender, and experimental vehicle were reviewed. No interactions were found to be significant via ANOVA. Tables G.1 through G.3 in Appendix G show the mean duration, urgency, and severity for the two-way combinations of the independent measures.

Chi-square Results. As shown in Table 4.3, the frequency results for gender by route were significant, $\chi^2(1) = 158.90, p < 0.0001$. Females on the interstate ($N = 983$) completed more lane changes than did females on the highway ($N = 545$); however, males on the interstate ($N = 716$) completed fewer lane changes than did males on the highway ($N = 983$).

The gender by experimental vehicle interaction was also significant, $\chi^2(1) = 4.79, p = 0.03$; females in the sedan ($N = 809$) completed more lane changes than did females in the SUV ($N = 719$); however, males in the sedan ($N = 834$) completed fewer lane changes than did males in the SUV ($N = 865$). Three-way and four-way chi-square analysis were also considered; however, no further useful information was gained by attempting to interpret the results.

Table 4.3: Two-Way Distributions of Frequency for Route, Usual Vehicle, Gender, and Experimental Vehicle for All Slow Lead Vehicle Lane Changes.

Frequency		Usual Vehicle		Gender		Experimental Vehicle	
		SUV Driver	Sedan Driver	Male	Female	SUV	Sedan
Route	Interstate	705	994	716	983	845	854
	Highway	625	903	983	545	739	789
Usual Vehicle	SUV Drv			715	615	659	671
	Sedan Drv			984	913	925	972
Gender	Male					865	834
	Female					719	809

Gray and Bold Italics = significant main effect of $p \leq 0.001$. Gray = significant main effect of $p \leq 0.05$.

Severity and Urgency

Table 4.4 lists the frequency and mean duration of lane changes for severity, urgency, and severity and urgency combinations. For severity, 92.7% of lane changes were rated with a severity of 1, and events rated with a severity of 5 were the next most common type (5.45%). As a reminder, events rated as a 5 for severity included lane changes in which another vehicle was present in the proximity zone (from 4 feet in front of the SV to within 30 feet of the rear of the SV) in the adjacent lane at the start of the lane change. In terms of urgency, 91.2% of lane changes were rated as having an urgency of 1. Urgency was an indicator of how soon the lane change was required; a small percentage (8.76 %) of lane changes took place relatively quickly (i.e., $TTC < 5.5$ s). Events rated low in both severity and urgency (i.e., 1 and 1) accounted for 85.2% of the total set of lane changes, which is yet another indication that most lane changes observed were relatively safe.

Table 4.4: Severity and Urgency Distributions for All Slow Lead Vehicle Lane Changes.

Severity and Urgency Rating Levels	Frequency	Percentage	Mean Duration*
Severity			
1	2,992	92.70%	6.26
2	55	1.70%	5.65
3	3	<0.10%	5.00
4	1	<0.10%	—
5	176	5.45%	6.56
6	—	—	—
7	—	—	—
Urgency			
1	2,944	91.23%	6.34
2	269	8.33%	4.98
3	14	0.43%	4.22
Severity x Urgency			
S = 1, U = 1	2,750	85.22%	6.34
S = 1, U = 2	232	7.19%	4.97
S = 1, U = 3	10	0.31%	8.70
S = 2, U = 1	52	1.61%	5.67
S = 2, U = 2	3	<0.1%	4.90
S = 2, U = 3	—	—	—
S = 3, U = 1	3	<0.1%	5.00
S = 3, U = 2	—	—	—
S = 3, U = 3	—	—	—
S = 4, U = 1	1	<0.1%	—
S = 4, U = 2	—	—	—
S = 4, U = 3	—	—	—
S = 5, U = 1	138	4.28%	6.80
S = 5, U = 2	34	1.05%	5.09
S = 5, U = 3	4	0.12%	4.52
S = 6, U = 1	—	—	—
S = 6, U = 2	—	—	—
S = 6, U = 3	—	—	—
Grand Total or Mean	3,227	100%	6.26

*Based on single lane changes.

Initial Direction of Maneuver

All of the slow lead vehicle lane changes were classified according to the initial direction of the maneuver. Table 4.5 provides the overall distribution of lane changes by direction. The large majority (91.7%) of lane changes were to the left. Lane changes to the left had a mean duration that was substantially longer as compared to lane changes to the right, $t(2166) = 3.31$, $p < .001$. As previously mentioned, most drivers spend their time in the right lane and pass slower vehicles on the left. Passing on the right was relatively rare and comprised less than 9% of the total set of slow lead vehicle lane changes.

Table 4.5: Direction Distributions for All Slow Lead Vehicle Lane Changes.

Lane change direction	Frequency	Mean Duration*	Mean Severity	Mean Urgency
Left	2,958	6.31	1.23	1.09
Right	269	5.78	1.34	1.16
Grand Total or Mean	3,227	6.26	1.24	1.09

*Duration for single lane changes only (N = 2,167).

The top portion of Table 4.6 shows the distribution of left and right slow lead vehicle lane changes by severity. Here, a familiar pattern can be observed: regardless of direction, most lane changes (92.9% to the left and 90.3% to the right) were rated low in severity (i.e., severity = 1). The bottom portion of the table shows the distribution of left and right slow lead vehicle lane changes across urgency categories. Here again, most lane changes (91.9% to the left and 84.4% to the right) were rated low in urgency.

Table 4.6: Severity and Urgency by Direction Distributions for Slow Lead Vehicle Lane Changes.

Severity Level	Left Lane Changes		Right Lane Changes	
	Frequency	Mean Duration	Frequency	Mean Duration
1	2,749	6.31	243	5.76
2	51	5.71	4	4.83
3	3	5.00	0	—
4	1	26.30	0	—
5	154	6.60	22	6.27
6	0	—	0	—
7	0	—	0	—
Urgency Level				
1	2,717	6.37	227	5.96
2	228	5.06	41	4.74
3	13	8.70	1	N/A
Grand Total or Mean	2,958	6.31	269	5.78

Success/Magnitude Distributions

As previously mentioned, the entire set of slow lead vehicle lane changes included predominantly single lane changes; there were there were 2,168 (67.2%) single slow lead vehicle lane changes. Passing and multiple lane change maneuvers were also analyzed; however, only the initial pass maneuver was analyzed in terms of independent variables such as velocity, range, and TTC. That is, the return maneuver portion of the lane change was not analyzed.

The Slow Lead Vehicle Lane Change Sample

The sample of slow lead vehicle lane changes was taken from the entire set of slow lead vehicle lane changes selected from all levels of success/magnitude. For cases in which passing or multiple lane change maneuvers were analyzed, only the initial pass maneuver was analyzed in terms of independent variables such as velocity, range, and TTC. That is, only the first lane change was evaluated, and the return maneuver portion of the lane change was not analyzed.

Selecting Maneuvers

Where possible, and until sample selection was complete, one maneuver was selected for each participant and for each experimental vehicle that the participant drove (SUV and sedan). This occurred for each group of maneuvers (i.e., low severity, moderate severity, high severity, and baseline) More specifically, one maneuver was selected that was performed by participant #2 in the sedan, one maneuver was selected that was performed by participant #2 in the SUV, one maneuver was selected that was performed by participant #3 in the sedan, and so on until the entire sample of 40 maneuvers was selected. The sample of 120 slow lead vehicle lane changes is referred to as the “sample,” and the set of 40 baseline (straight-ahead) events are referred to as “baseline.”

For cases rated as moderate or high in urgency or severity, not all participants had lane changes to include in the sample. This was due to the observation that some participants drove more conservatively and therefore displayed fewer (or no) lane changes that were urgent or severe. As previously described, a form of matched and stratified sampling was used to select maneuvers from each group. Where possible, samples were obtained to include all participants. In some cases, a selected maneuver was unusable (e.g., due to missing video data). In this case, the next available maneuver was selected that matched the criteria of the unusable maneuver. Figure 3.23 can be reviewed in the context of the following descriptions.

For maneuvers rated with severity = 5, a sample of maneuvers was selected (Note: there were none rated severity > 5). Maneuvers were selected to equally represent all levels of urgency when possible. For maneuvers rated as urgency ≥ 3 , all four maneuvers were selected. For those rated as urgency = 2, 17 maneuvers were selected so that at least one maneuver was selected for each participant who had a maneuver in this category (Note: not all drivers had a maneuver rated with severity = 5). Maneuvers were then selected to be representative of the remainder in that category (e.g., participants 12 and 15 had a large percentage of the total in this category, so more lane changes were selected for those participants). For those maneuvers rated as urgency = 1, a sample of 19 maneuvers was selected. Thus, 41 maneuvers* (4 + 17 + 20) representing the range of urgency ratings for severity = 5 were selected.

For maneuvers in which $2 \leq$ severity rating ≤ 4 , maneuvers were selected in a similar manner. No maneuvers had urgency ratings ≥ 3 in this case. For maneuvers rated as urgency = 2, all three maneuvers were selected. For those rated as urgency = 1 and severity = 4, the only

available maneuver (1) was selected. For those rated as urgency = 1 and severity = 3, all three maneuvers were selected. For those maneuvers rated as severity = 2, a total of 33 maneuvers were systematically selected out of the 52 available that meet this criteria. Thus, 39 maneuvers (3 + 1 + 3 + 32) representing the range of urgency ratings for $2 \leq \text{severity} \leq 4$ maneuvers were selected. As a reminder, one maneuver originally classified with a $2 \leq \text{severity} \leq 4$, was later reclassified as a severity = 5 event, so not exactly 40 events exist in each category of severity.

For maneuvers rated as severity = 1, a total of 40 maneuvers was selected. For those with urgency ≥ 3 , all 9 maneuvers were included; of those rated with urgency = 2, 16 out of 19 of the maneuvers were included; of those rated with urgency = 1, 15 out of 32 of the maneuvers were included. Thus, 40 maneuvers (9 + 16 + 15) were selected representing the range of urgency ratings for severity = 1.

Where possible, a sample was selected that represented a wide number of participants. Figure 4.6 illustrates the percentage of total available slow lead vehicle lane changes (out of 3,227), as compared to the sample selected (N = 120). Investigation of this figure shows that the percentage of lane changes selected was similar for most participants. This was except, for example, for participants 8, 15, and 9, where a larger percentage of lane changes was present in the sample. The reason that larger proportions of the total were represented was because in most cases, these particular drivers performed lane changes that were rated high in urgency as well. For example, of the total number of slow lead vehicle lane changes rated high in urgency, 6 out of 13 (46%) of the lane changes were performed by participant #8. For participant #8, the percentage of lane changes for all slow lead vehicle lane changes was 6.4% for the entire available set and 10.8% for the sample. The reason that a higher percentage of lane changes was included in the sample was because this participant did not display any events rated between 2 and 4 in severity. For this reason, a larger number of events rated low in severity were included in the sample (17.5% for the sample vs. 6.5% all available data for events rated with severity = 1). Other examples include participants 4 and 17, who performed no lane changes rated high in severity (severity = 5) and participants 10 and 11, who had very few in the total set of lane changes (and none in the sample). Likewise, participants 4 and 8 displayed no lane changes that were rated moderately (severity 2 to 4).

Investigation of Figures 4.7, 4.8, and 4.9 and Table 4.7 may lead to a better understanding of how the percentage of the total available compared to the sample at each level of severity.

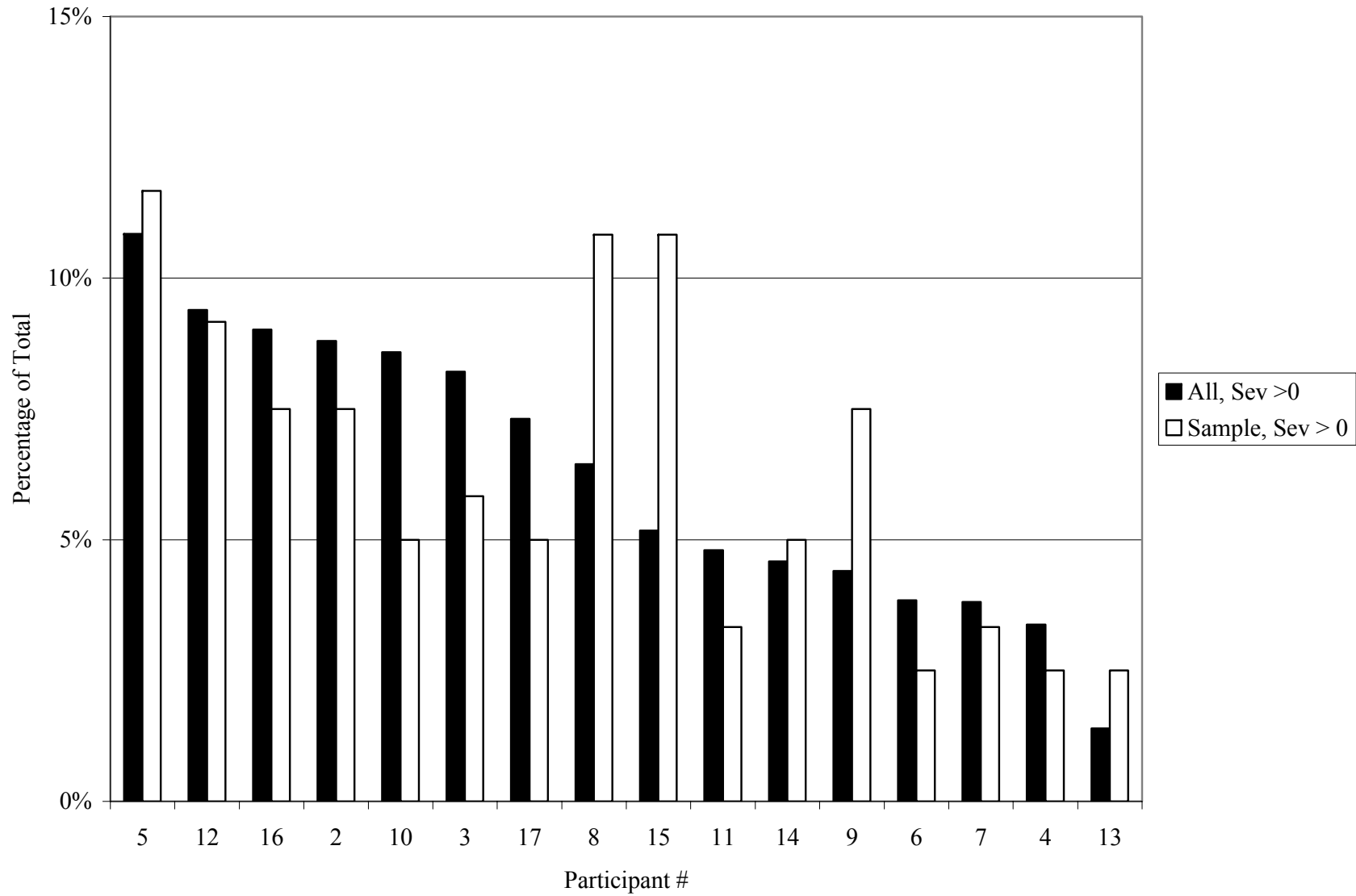


Figure 4.6. Percentage of All Available Slow Lead Vehicle Lane Changes vs. the Sample Selected for all Participants.

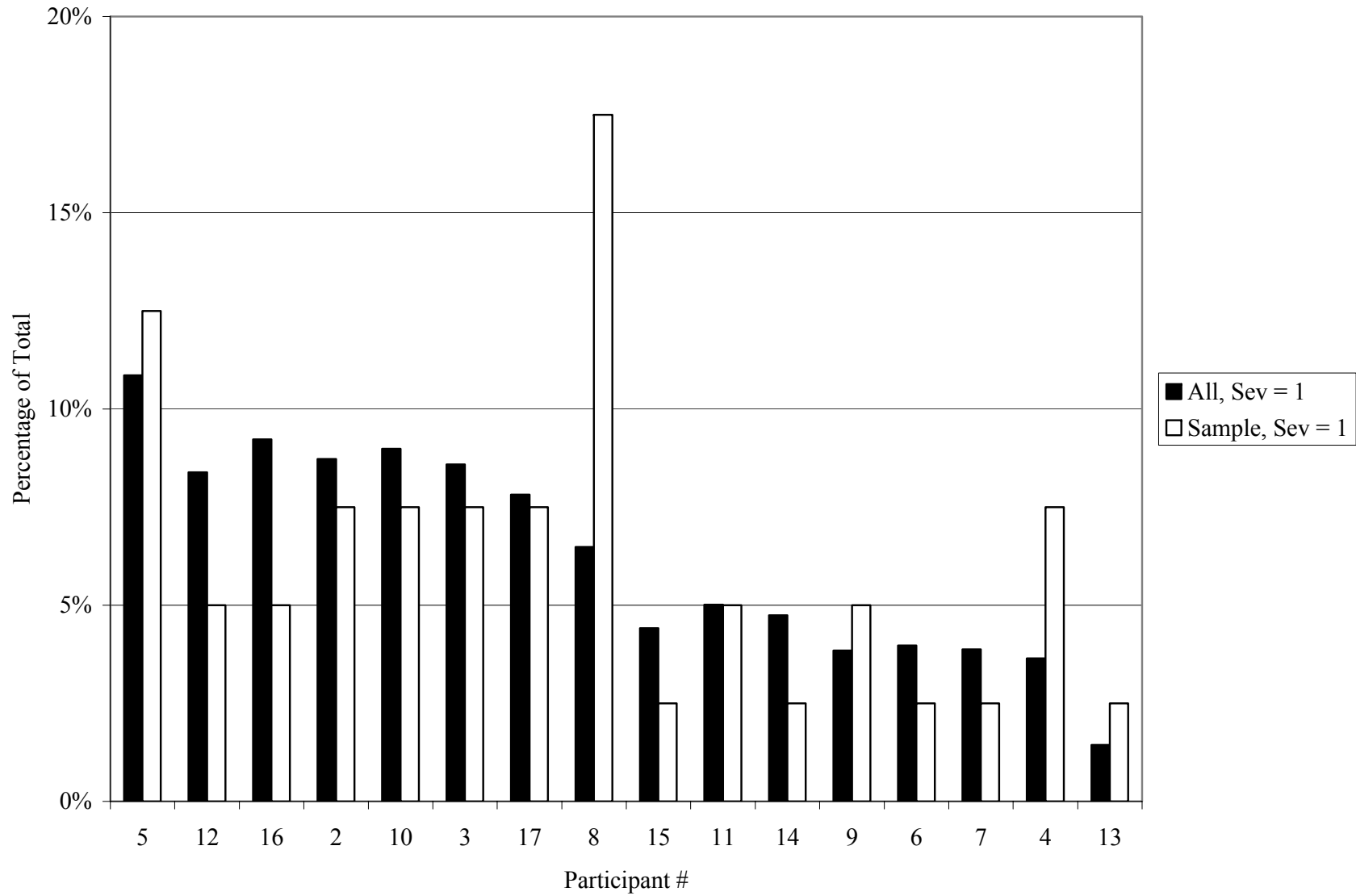


Figure 4.7. Percentage of all Available Slow Lead Vehicle Lane Changes vs. the Sample Selected for Severity = 1.

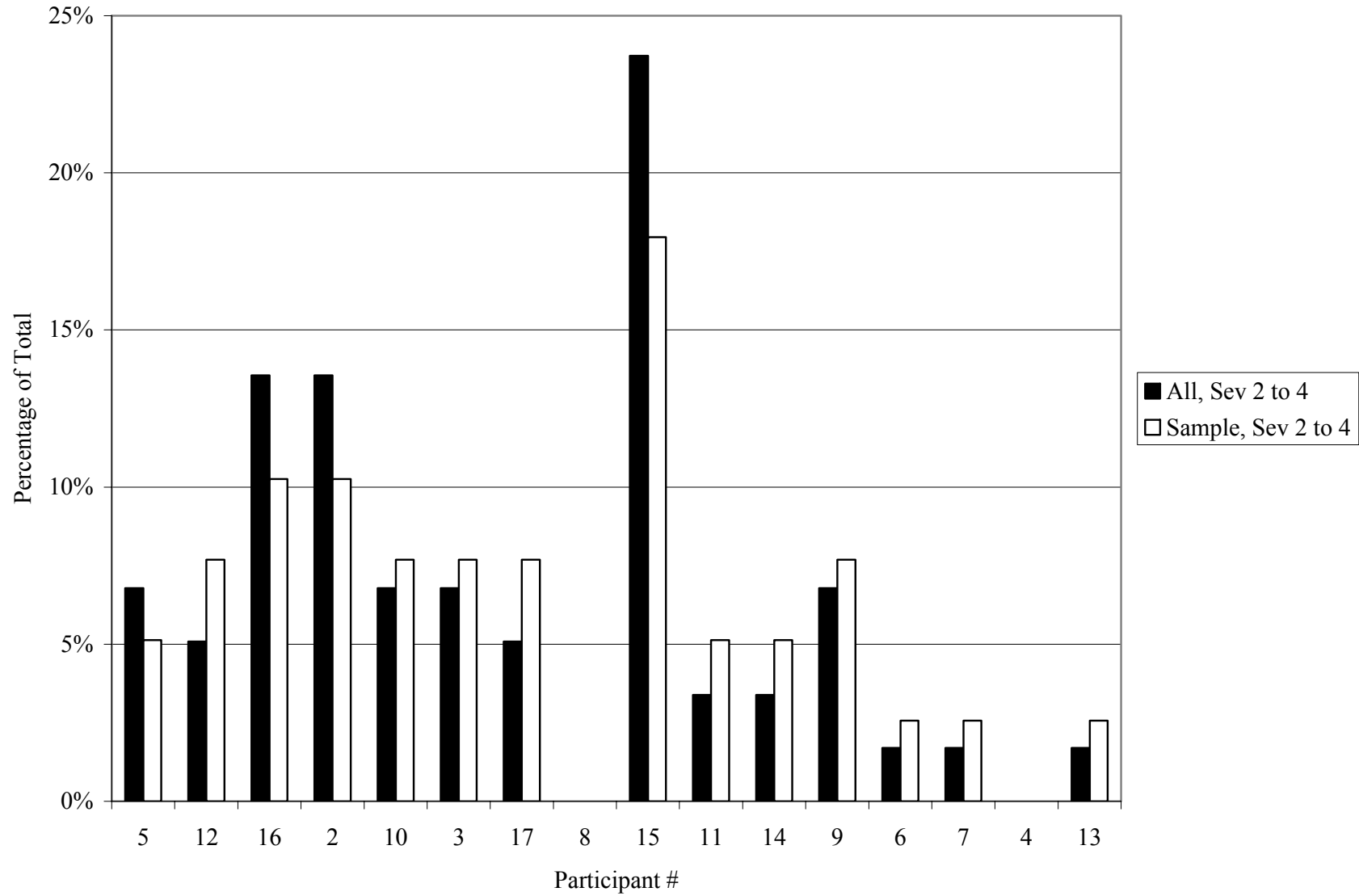


Figure 4.8. Percentage of all Available Slow Lead Vehicle Lane Changes vs. the Sample Selected for $2 \leq \text{Severity} \leq 4$.

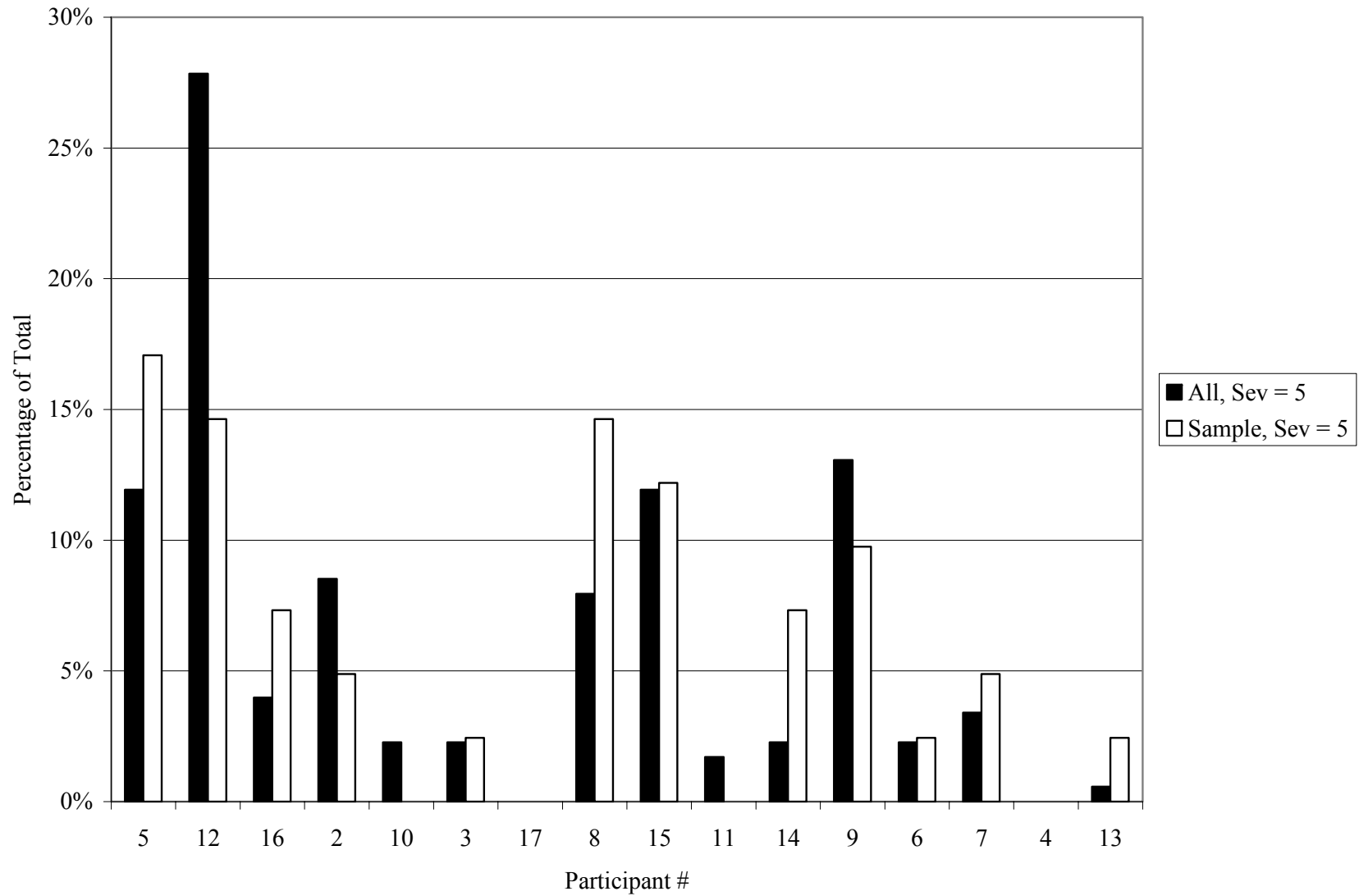


Figure 4.9. Percentage of all Available Slow Lead Vehicle Lane Changes vs. the Sample Selected for Severity = 5.

Table 4.7: Percentages in Rank Order of all Available Slow Lead Vehicle Lane Changes vs. the Sample Selected for Each Participant.

Severity	All		1		2 to 4		5	
	Total	Sample	Total	Sample	Total	Sample	Total	Sample
Partic. #	N=3,227	N=120	N=2,993	N=40	N=59	N=39	N=176	N=41
5	10.8%	11.7%	10.9%	12.5%	6.8%	5.1%	11.9%	17.1%
12	9.4%	9.2%	8.4%	5.0%	5.1%	7.7%	27.8%	14.6%
16	9.0%	7.5%	9.2%	5.0%	13.6%	10.3%	4.0%	7.3%
2	8.8%	7.5%	8.7%	7.5%	13.6%	10.3%	8.5%	4.9%
10	8.6%	5.0%	9.0%	7.5%	6.8%	7.7%	2.3%	0.0%
3	8.2%	5.8%	8.6%	7.5%	6.8%	7.7%	2.3%	2.4%
17	7.3%	5.0%	7.8%	7.5%	5.1%	7.7%	0	0
8	6.4%	10.8%	6.5%	17.5%	0	0	8.0%	14.6%
15	5.2%	10.8%	4.4%	2.5%	23.7%	17.9%	11.9%	12.2%
11	4.8%	3.3%	5.0%	5.0%	3.4%	5.1%	1.7%	0
14	4.6%	5.0%	4.7%	2.5%	3.4%	5.1%	2.3%	7.3%
9	4.4%	7.5%	3.8%	5.0%	6.8%	7.7%	13.1%	9.8%
6	3.8%	2.5%	4.0%	2.5%	1.7%	2.6%	2.3%	2.4%
7	3.8%	3.3%	3.9%	2.5%	1.7%	2.6%	3.4%	4.9%
4	3.4%	2.5%	3.6%	7.5%	0	0	0	0
13	1.4%	2.5%	1.4%	2.5%	1.7%	2.6%	0.6%	2.4%

Shading indicates percentages $\geq 7.5\%$ or the 6 largest categories for each pair of comparisons

Analysis was based on the sample of 120 slow lead vehicle lane changes and the baseline events. For both the sample and the baseline events, chi-square analyses and ANOVAs were conducted in a manner similar to those conducted for the large set. In addition, data analyses were expanded to include range and TTC to the lead vehicle and the rear adjacent vehicle; turn signal activation and timing; steering, braking, and lateral acceleration; and the glance direction and duration of glances.

Main Effects

Analysis of the sample revealed that the sample was representative of the large set of lane changes. Results for the ANOVA revealed that there were no significant main effects or interactions for duration. Overall, single lane changes had a mean duration of 5.58 s ($SD = 1.33$).

As with the large set, route was significant for urgency, $F(1, 31) = 9.62, p = 0.02$, and interstate lane changes were rated lower in urgency than highway lane changes. For interstate lane changes, the mean urgency was 1.3 ($SD = 0.50$), and for highway lane changes, the mean urgency was 1.8 ($SD = 0.80$), as illustrated by Figure 4.10.

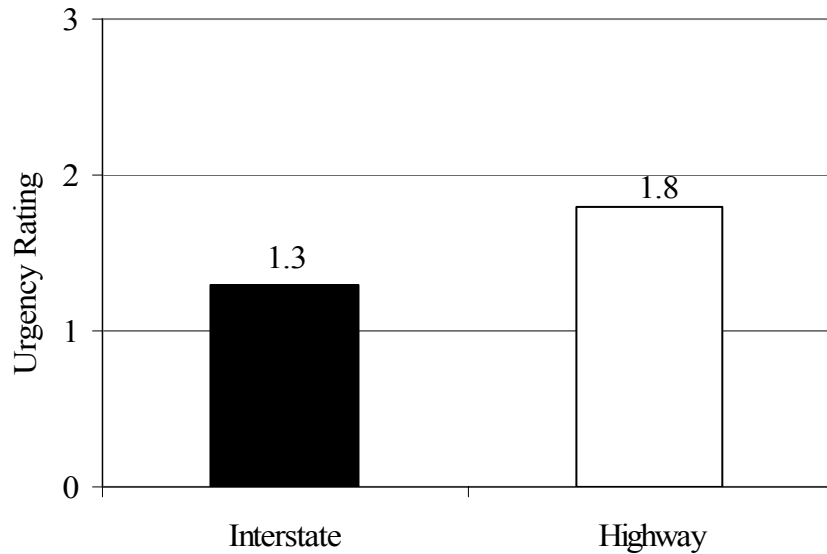


Figure 4.10. Mean Urgency Ratings for Route for the Sample.

Two other differences were found for the sample, in terms of usual vehicle. Usual vehicle was significant for duration, $F(1, 8) = 6.80, p = 0.03$; SUV drivers had a mean of 6.0 s, and sedan drivers had a mean duration of 5.3 s. Usual vehicle was also significant for urgency, $(1, 8) = 11.08, p = 0.01$. SUV drivers had a mean urgency rating of 1.3 ($SD = 0.51$), and sedan drivers had a mean urgency rating of 1.7 ($SD = 0.75$). However, these differences were not present for the large set. There were no other significant main effects. Appendix H shows for the SAS code and results.

Chi-square Results. Chi-square results for the sample reflect what was discovered for the large set of lane changes. Drivers on the interstate completed 65 lane changes, while drivers on the highway completed 55 lane changes. However, this difference was not statistically significant for the sample. The lack of frequency differences for the sample was likely caused by the stratified sampling method used. Sampling was completed so that an essentially equal set of lane changes for each route was selected, where possible. This was done to assure that a wide variety of maneuvers could be represented in terms of the independent measures.

On the other hand, usual vehicle was significant for both the large set of lane changes and the sample. For the sample, analyses showed that usual vehicle was significant, $\chi^2(1) = 4.80, p < 0.028$. There were 48 lane changes completed by SUV drivers and 72 lane changes completed by sedan drivers, as illustrated by Figure 4.11.

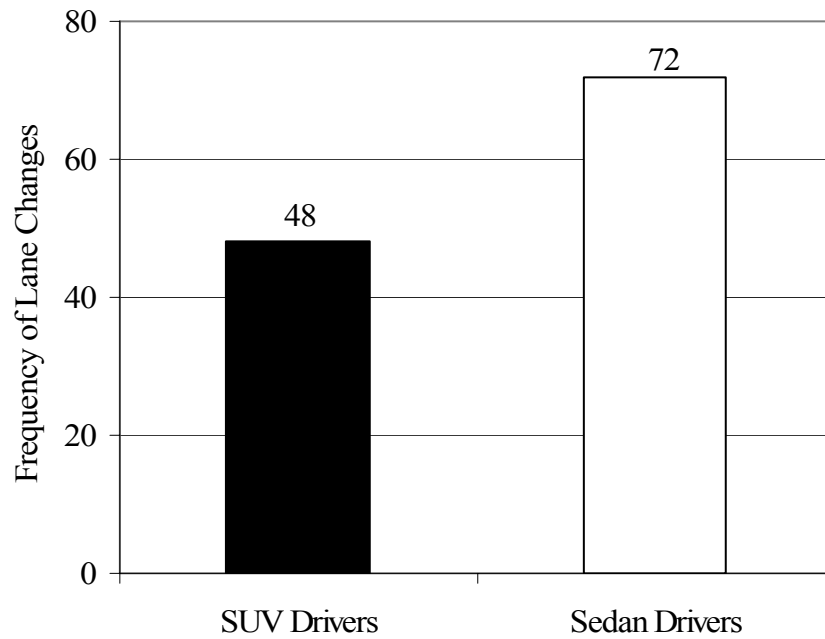


Figure 4.11. Frequency of Lane Changes for Usual Vehicle for Sample.

Gender was also significant, $\chi^2(1) = 6.5333$, $p = 0.0106$; there were 74 lane changes completed by male drivers and 46 lane changes completed by female drivers, as illustrated by Figure 4.12. Table 4.8 illustrates the overall results for the sample (in a manner similar to that of Table 4.1 for the larger set).

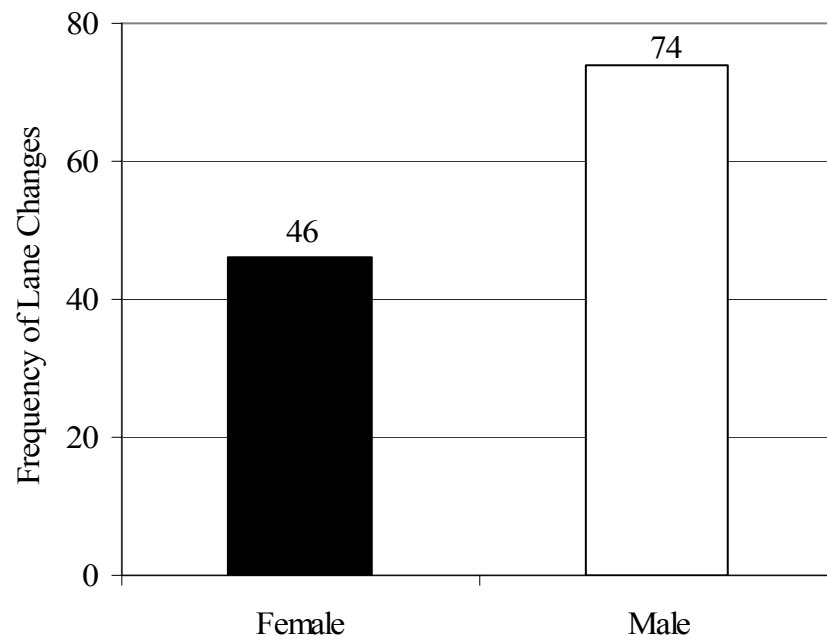


Figure 4.12. Frequency of Lane Changes for Gender for Sample.

Table 4.8: Means Distributions for Route, Usual Vehicle, Gender, and Experimental Vehicle for Slow Lead Vehicle Lane Change Sample (N = 120).

Independent Variables	Level	Dependent Variables			
		Mean Duration (Seconds) (StDev)	Mean Urgency (1-4) (StDev)	Mean Severity (1-7) (StDev)	Frequency (Percent of total)
Route	Interstate	5.75 (1.18)	1.32 <i>(0.50)</i>	2.95 (1.67)	65 (54.17%)
	Highway	5.37 (1.48)	1.75 <i>(0.80)</i>	2.47 (1.75)	55 (45.83%)
Usual Vehicle	SUV Driver	6.04 (1.24)	1.31 <i>(0.51)</i>	2.73 (1.63)	48 (40.00%)
	Sedan Driver	5.29 (1.32)	1.65 <i>(0.75)</i>	2.74 (1.78)	72 (60.00%)
Gender	Male	5.74 (1.11)	1.61 (0.74)	2.92 (1.77)	74 (61.67%)
	Female	5.48 (1.45)	1.37 (0.57)	2.43 (1.61)	46 (38.33%)
Experimental Vehicle	SUV	5.41 (1.14)	1.49 (0.70)	2.75 (1.72)	61 (50.83%)
	Sedan	5.75 (1.49)	1.54 (0.68)	2.71 (1.73)	59 (40.17%)
Grand Total or Mean (StDev)		5.58 (1.33)	1.52 (0.69)	2.73 (1.72)	120

Gray Bold and Italics = significant main effect of $p \leq 0.05$.

Interaction Effects

ANOVA & chi-square Results. There were no significant two-way interactions for either the ANOVA or the two-way chi-square analyses for frequency. Frequency results are displayed in Table H.4 through Table H.7 of Appendix H.

Severity and Urgency

Table 4.9 lists the frequency and mean duration of lane changes for severity, urgency, and severity and urgency combinations. For severity, most events were rated as 1, 2, or 5 (96.6%), with the remainder rated as either 3 or 4 (3.3%). In terms of urgency, 59.2% of lane changes were rated as urgency of 1, 30.0% of events were rated with urgency of 2, and 10.8% of events were rated with urgency of 3.

Table 4.9: Severity and Urgency Distributions for Slow Lead Vehicle Lane Change Sample.

Severity and Urgency Rating Levels	Frequency	Percentage	Mean Duration*
Severity			
1	40	33.3%	5.40
2	35	29.2%	5.73
3	3	2.5%	5.00
4	1	0.8%	6.50
5	41	34.2%	5.64
6	—	—	—
7	—	—	—
Urgency			
1	71	59.2%	5.98
2	36	30.0%	4.96
3	13	10.8%	5.15
Severity x Urgency			
S = 1, U = 1	15	12.5%	5.81
S = 1, U = 2	16	13.3%	4.88
S = 1, U = 3	9	7.5%	5.66
S = 2, U = 1	32	26.7%	5.77
S = 2, U = 2	3	2.5%	5.33
S = 2, U = 3	—	—	—
S = 3, U = 1	3	2.5%	5.00
S = 3, U = 2	—	—	—
S = 3, U = 3	—	—	—
S = 4, U = 1	1	0.8%	6.50
S = 4, U = 2	—	—	—
S = 4, U = 3	—	—	—
S = 5, U = 1	20	4.28%	6.53
S = 5, U = 2	17	1.05%	4.98
S = 5, U = 3	4	0.12%	4.00
S = 6, U = 1	—	—	—
S = 6, U = 2	—	—	—
S = 6, U = 3	—	—	—
Grand Total or Mean	120	100%	5.58

*Based on single lane changes.

Initial Direction of Maneuver

The sample of slow lead vehicle lane changes was also classified according to the initial direction of the maneuver. Table 4.10 provides the overall distribution of lane changes by direction. The large majority of lane changes were to the left (94.2%). Lane changes to the left had a mean duration that was slightly but not significantly longer, as compared to lane changes to the right, which followed the same patterns as was discovered for the large set.

Table 4.10: Direction Distributions for Slow Lead Vehicle Lane Change Sample.

Lane change direction	Frequency	Mean Duration	Mean Severity	Mean Urgency
Left	113	5.61	2.66	1.48
Right	7	5.07	3.86	2.14
Grand Total or Mean	120	5.58	2.73	1.52

Success/Magnitude Distributions

The proportion of single slow lead vehicle lane changes followed the pattern observed in the large set of slow lead vehicle lane changes, in that single lane changes were the largest category. For the sample, there were 93 (77.5%) single lane changes.

Comparison Between the Large Set and Sample Set

The sample set of lane changes was representative of the large set in many aspects, as illustrated by Table 11. In one case, in terms of lane change frequency, significant differences were revealed for the large set, but only a possible trend was apparent for the sample. The main difference between the large and small set was the predominance of events rated low in severity and urgency in the large set. The large set of lane changes had 85% of cases rated low in both severity and urgency, whereas the sample only had 13% of cases rated low. This was due to the stratified sampling used, in which a large variety of lane changes were represented, including the high severity and high urgency cases.

Additional analyses were conducted only on the sample using the lane change reduction program. In-depth analyses included turn signal use, eye glance patterns, and predictive model development, as described in the following sub-sections.

Table 4.11: Similarities Between Large Set and Sample Set of Lane Changes.

	Large Set	Sample Set
Mean Duration	6.3 s	5.6 s
Urgency: Route	Interstate < Highway	Interstate < Highway
LC Frequency: Route	Interstate > Highway	Interstate > Highway (n.s.)
LC Rate per mile: Route	Interstate < Highway	N/A
LC Frequency: Usual Vehicle	SUV Drivers < Sed Drivers	SUV Drivers < Sed Drivers
LC Frequency: Gender	Males > Females	Males > Females
Mean Severity	1.24	2.73
Mean Urgency	1.09	1.52
Initial Direction	92% to left	94% to left
Success/Magnitude	67% Single	78% Single

Turn Signal Use

Turn signal use and timing were analyzed as well. This was addressed first by identifying lane change cases in which the turn signal was active at t_0 and looking at turn signal timing prior to or just after t_0 . In terms of turn signal use, analysis showed that turn signals were activated at t_0 only 40.8% of the time. Each lane change was then reviewed to determine the exact time that the turn signal was activated either before or *after* t_0 . For each maneuver, the timing of lane signal activation was represented by a negative or positive value in seconds. Negative values were associated with the amount of time *before* the lane change took place, and positive values were associated with the amount of time *after* the lane change took place. For example, if the value was -0.6 seconds, this indicated that the turn signal was activated 0.6 seconds before the lane change initiation point (t_0). An activation value of 0.4 seconds indicated that the turn signal was activated 0.4 seconds after t_0 .

It was discovered that drivers activated the turn signal as part of the lane change in 77 out of 120 (64.2%) cases. The mean timing was -0.58 s ($SD = 1.21$ s), indicating that, on average, drivers signaled just prior to t_0 . The minimum was -5.6 s and the maximum was 1.9 s. Thus, drivers used turn signals in 64.2% of the cases, and in most cases, drivers used turn signals prior to the start of the lane change, as illustrated by Figure 4.13.

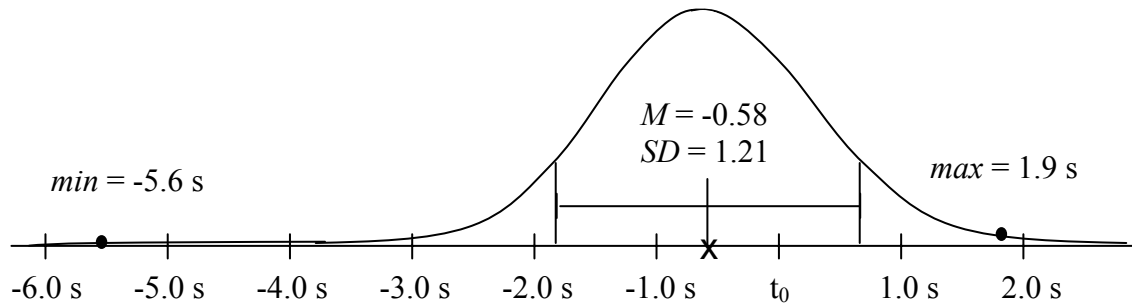


Figure 4.13. Mean Turn Signal Timing for Cases in which Turn Signals were Activated, Showing Mean, Standard Deviation, Minimum, and Maximum.

Another way to view these data is by looking at turn signal use by participant. Table 4.12 illustrates the turn signal use and mean timing for the sample of lane changes. For example, participants 14, 8, 2, and 10 (25% of all participants) used turn signals for fewer than 17% of the analyzed lane changes, while participants 3, 6, 7, 9, 13, and 17 (38% of all participants) used turn signals in 100% of the cases.

Table 4.12: Participant Turn Signal Use and Mean Timing.

Participant #	Off	%	On	%	Total	Mean Timing
14	6	100.0%	0	0.0%	6	—
8	12	92.3%	1	7.7%	13	0.20
2	8	88.9%	1	11.1%	9	0.20
10	5	83.3%	1	16.7%	6	1.90
11	2	50.0%	2	50.0%	4	0.00
4	1	33.3%	2	66.7%	3	-1.05
15	3	23.1%	10	76.9%	13	-1.16
16	2	22.2%	6	77.8%	9	-0.13
12	2	18.2%	9	81.8%	11	-1.43
5	2	14.3%	10	85.7%	14	-0.22
3	0	0.0%	7	100.0%	7	-0.43
6	0	0.0%	3	100.0%	3	0.27
7	0	0.0%	4	100.0%	4	-0.70
9	0	0.0%	9	100.0%	9	0.10
13	0	0.0%	3	100.0%	3	-1.13
17	0	0.0%	6	100.0%	6	-1.57
Total	43	35.8%	77	64.2%	120	-0.58

Turn Signal Use in Comparison with Severity and Urgency

To expose the relationship between turn signal use and maneuver criticality, Table 4.13 illustrates the relationship between turn signal use and severity rating. For lane changes rated with a severity of 1, turn signals were used in 55% of the cases. A similar pattern can be seen for each of the three categories of severity in terms of percentage of turn signal use, presented in descending order. The results seem to indicate that drivers used turn signals more often when the severity was moderate (i.e., a vehicle was likely to be present in the FAZ). For cases in rated high in severity, turn signals were used in 56% of the cases.

Table 4.13: Turn Signal Use by Severity Rating.

Severity	Off	On	Total
1	18 (45.0%)	22 (55.0%)	40
2 to 4	7 (18.0%)	32 (82.0%)	39
5	18 (43.9%)	23 (56.1%)	41
Total	43 (35.8%)	77 (64.2%)	120

Table 4.14 illustrates the relationship between turn signal use and urgency. Here, one can observe that of 13 total cases rated urgency 3, turn signals were used in only 38% of cases. However, for the most common lane change urgency (i.e., those rated urgency 1), 31% did not have a turn signal indicator on at any time during latency or just after t_0 . Since the urgency ratings refer to the SV's relationship to a lead vehicle, the lack of turn signal use for urgencies of 3 is not surprising. It is possible that drivers did not use signals since these lane changes may have been "last minute" or otherwise fast maneuvers for which the driver may not have felt there was enough time to signal. It is also possible that no other vehicles were around to see a turn signal, had it been activated.

Table 4.14: Turn Signal Use by Urgency Rating.

Urgency	Off	On	Total
1	22 (33.0%)	49 (69.0%)	71
2	13 (36.1%)	23 (63.9%)	36
3	8 (61.5%)	5 (38.5%)	13
Total	43 (35.8%)	77 (64.2%)	120

Perhaps one of the most complex relationships is that between turn signal use and the combination of severity and urgency ratings. Tables 4.15 through 4.17 illustrate this relationship. For lane changes rated urgency 1 and severity 5, only 50% had the signal activated. For lane changes rated urgency 2 (at any level of severity), 64% had the turn signal activated. Where the lane change had an urgency of 3, drivers used the turn signals more often when a vehicle was present in the PZ or FAZ (50%) rather than when no such vehicle was present (33%). Note: the number of observations in these categories is small. In addition, 6 out of 13 events rated with urgency = 3 were performed by participant number 8, who rarely used a turn signal.

Table 4.15: Turn Signal Use by Severity where Urgency = 1.

Urgency	Severity	Off	On	Total
1	1	40.0%	60.0%	15
	2 to 4	16.7%	83.3%	36
	5	50.0%	50.0%	20
	Total	31.0%	69.0%	71

Table 4.16: Turn Signal Use by Severity where Urgency = 2.

Urgency	Severity	Off	On	Total
2	1	37.5%	62.5%	16
	2 to 4	33.3%	66.7%	3
	5	35.3%	64.7%	17
	Total	36.1%	63.9%	36

Table 4.17: Turn Signal Use by Severity where Urgency = 3.

Urgency	Severity	Off	On	Total
3	1	66.7%	33.3%	9
	2 to 4	—	—	0
	5	50.0%	50.0%	4
	Total	61.5%	38.5%	13

Cases in Which No Turn Signal was Used. The previous results indicate that there is an inverse relationship between turn signal use and urgency rating--as urgency rises, the likelihood that a driver will use the turn signal lowers. This leads to an interesting issue that emerged from these analyses: “Why do people not signal?” Although this issue cannot be directly answered, further analysis of the lane changes in which no signal was used may offer some insight into this issue.

Of the 120 lane changes, 43 (35.8%) were cases in which a turn signal was not used at any time prior to or during the lane change. This set of lane changes was reviewed to determine what was surrounding the vehicle when the lane change occurred. Of these 43 lane changes, 13 (30%) did not have vehicles present prior to t_0 . In other words, no other vehicles were near the SV at the time during which a turn signal might have been activated. For the remaining 30 cases, however, this was not true.

In 11 (26%) of the cases, a vehicle was present in the adjacent lane (FAZ or PZ) at t_0 and no signal was used. That is, a vehicle was in the adjacent destination lane, and the driver changed lanes in front of that vehicle. Table 4.18 illustrates these cases in terms of the distance in feet from the SV. For this case, the mean distance was 79.4 feet ($SD = 58.9$ feet), including one case in which the SV was as close as 10 feet to the POV at t_0 . There were also 11 cases (26%) in which no signal was used and the lane change was initiated just after a vehicle passed the SV, and the SV followed closely behind the POV ($M = 11$ feet, $SD = 6.5$ feet). In seven cases (16%), another vehicle was behind the SV in the same (original) lane as the SV at t_0 and no signal was used ($M = 210.9$ feet, $SD = 105.8$ feet). There was one case in which a turn signal was not used. In this case, a vehicle was just starting to turn onto the road, behind the SV, when the SV passed.

Table 4.18: Distance Statistics in Feet for Lane Changes in Which No Turn Signal was Used.

Description	N	Percent	Avg. Dist.	SD	Min	Max	Range
Pull behind Vehicle after it Passes SV	11	25.6%	11.0	6.53	2.0	22.0	20.0
Vehicle in Rear Adjacent Lane	11	25.6%	79.4	58.9	10.0	187.0	177.0
Vehicle Directly Behind SV	7	16.4%	210.9	105.8	75.0	362.0	287.0
Vehicle Starting to Pull Onto Road	1	2.3%	90.9	NA	90.9	90.9	0.0
SUBTOTAL, Vehicles Present	30	69.8%	85.4	97.2	2.0	362.0	360.0
SUBTOTAL, No Vehicles Behind/Beside SV	13	30.2%	NA	NA	NA	NA	NA
TOTAL Cases with No Signals	43	100.0%	NA	NA	NA	NA	NA

The question “Why do people not signal?” cannot be directly answered; however, for cases in which no turn signal was used, 30% of cases did not have other vehicles beside or behind the SV when the lane change was initiated. In 44% (19) of the cases, a vehicle *was* behind the SV, and a signal was not used. In 26% of cases the SV pulled behind another vehicle just after it passed by.

A final question was asked during analysis: When turn signals are used, how often is a blind spot check made or not made? To address this, descriptive statistics were tabulated. Results indicated the following. Out of a total of 77 lane changes in which turn signals were used, 60% (46) were not accompanied by a blind spot check. That is, 40% of cases had both a turn signal and a blind spot check while performing the lane change.

Eye Glance Patterns

Eye glance patterns were identified and analyzed to obtain a better understanding of driver visual behavior during lane change latency. It is likely that drivers exhibit specific eye glance patterns prior lane change initiation (Tijerina et al., 1997). Identifying these patterns may lead to insights as to when drivers are preparing to change lanes based on the timing of glances. This information will be important in the development of CAS displays in terms of display location, timing of warning/alert information, and overall system design. Additionally, studying glance patterns may assist CAS developers in determining the “last second” that a warning/alert must be issued to assist the driver in making a decision.

Eye glance location was analyzed for the three seconds prior to lane change initiation. Thus, the definition of lane change latency is further refined as the three-second time period before lane change initiation during which specific eye behaviors could be observed. Three seconds was selected for analysis since critical driver decisions must be made during that time period, and this period is adequate to capture most of the relevant scanning behaviors (Lee, Olsen & Wierwille, 2003). Glance positions of interest included center forward, rearview mirror, left mirror, right mirror, left window, right window, instrument cluster, left blind spot, right blind spot, other interior, and indeterminate, as listed in Table 4.19.

Glance data from the current field study were analyzed in a manner similar to that of Tijerina et al. (1997) and as reported by Lee, Olsen and Wierwille (2003); glance location was evaluated in terms of the proportion of times that at least one glance occurred to a particular

location. The highest proportion was associated with glancing forward (first column of Table 4.19 with at least one glance to the forward view for 99% of events during latency).

Data were also available for eye glance duration for various locations of interest. Eye glance durations include the transition time to the location of interest. These glances occurred during the 3 seconds prior to the beginning of the lane change; however, if there was a glance in progress at t_{-3} or at t_0 , the analysis was extended to cover those complete glances (i.e., the glances were not arbitrarily cut off at t_{-3} or t_0). The mean analyzed duration was 4.7 s per event due to this inclusion policy, rather than an even 3.0 s.

Number of Glances. There were a total of 544 glances across the 120 lane changes, with a mean of 4.5 glances per lane change event. The highest mean number of glances was 2.3 to the forward location (275 glances divided by 120 lane change events). The percent of total glances for the forward glance location was 50.6% (275 glances divided by 544 glances). Out of 120 slow lead vehicle lane changes, 99% of lane changes had at least one glance to the forward view (i.e., 119 instances out of 120 lane changes) during latency (one instance was indeterminate). Large proportions of glances were allocated for glances to the rearview mirror and the left mirror as well, as illustrated by Table 4.19.

Table 4.19: Number of Glances Statistics for the Sample of Lane Changes, All Glance Locations for the 3 Seconds Prior to t_0 (120 events).

Glance location	Glance proportion during latency	Events w/ at least 1 glance	Mean Number Glances/ Event	Total Number of glances	Percent of Total number of Glances
Forward (F)	0.99	119	2.29	275	50.6%
Rearview Mir. (RVM)	0.46	55	0.63	76	14.0%
Left Mirror (LM)	0.50	60	0.66	79	14.5%
Left Window (LW)	0.27	32	0.33	40	7.4%
Left Blind Spot (LBS)	0.28	34	0.31	37	6.8%
Instrum. Cluster (IC)	0.18	22	0.21	25	4.6%
Right Mirror (RM)	0.04	5	0.04	5	0.9%
Right Window (RW)	0.01	1	0.02	2	0.4%
Right Blind Spot (RBS)	0.02	2	0.03	3	0.6%
Other Interior (OINT)	0.01	1	0.01	1	0.2%
Indeterminate (IND)	0.01	1	0.01	1	0.2%
All events	1.00	120	4.53	544	100.0%

Note: The following key was used for this and subsequent tables and figures:

F	Forward		
LW	Left window	RW	Right window
LM	Left mirror	RBS	Right blind spot
LBS	Left blind spot	RM	Right mirror
IC	Instrument cluster	RVM	Rear view mirror
OINT	Other interior	IND	Indeterminate

Glance Duration. Visual glance duration is the length of time spent looking at one direction, including movement time to the next location. Glances to the forward view had the highest mean single glance duration of 1.42 s (391.7 s/275 glances), as well as the highest overall glance duration per event, as illustrated by Table 4.20. That is, on average, each event had forward glances adding up to 3.26 s out of the total average of 4.72 s. The percent of glance duration was calculated as the total glance duration for a particular location divided by the total glance duration for all events. For forward this was 69.2% for forward (391.7 s/566.4 s). Rearview mirror and left mirror locations had relatively high values for percent of glance duration as well.

Table 4.20: Glance Duration Statistics for the Sample of Lane Changes, All Glance Locations for the 3 Seconds Prior to t_0 (120 events).

Glance location	Glance Duration/Event (sec)	Total Glance Duration	Percent of Glance Duration	Mean Single Glance Duration (duration/# glances) (sec)
F	3.26	391.70	69.2%	1.42
RVM	0.39	46.70	8.3%	0.61
LM	0.44	52.30	9.2%	0.66
LW	0.23	27.00	4.8%	0.68
LBS	0.19	23.30	4.1%	0.63
IC	0.12	14.00	2.5%	0.56
RM	0.02	2.80	0.5%	0.56
RW	0.01	1.70	0.3%	0.85
RBS	0.02	2.10	0.4%	0.70
OINT	0.01	0.60	0.1%	0.60
IND	0.04	4.20	0.7%	4.20
All events	4.72	566.40	100.0%	1.04

Glance Link Analysis. Glance link analysis was used to analyze eye glance patterns prior to lane change initiation in the manner described by Wierwille (1981) and conducted recently by Lee, Wierwille, and Olsen (2003). This analysis involves calculating link value probabilities, or the probability of a glance transition between two specific glance locations in the 3 seconds prior to lane change initiation. These probabilities do not indicate the order in which glances occurred but do indicate the likelihood of glancing from one glance location to another or vice versa as presented in Table 4.21.

Table 4.21: Link Probabilities between Eye Glance Locations for Slow Lead Vehicle Lane Changes (N = 120).*

	LW	LM	F	RVM	RM	RW	RBS	IC
LBS	0.02	0.05	0.05					
LW		0.02	0.11	0.01				0.01
LM			0.27	0.01				
F				0.30	0.02	0.01	0.02	0.09
RVM					0.01			0.01

The glance proportions from Tables 4.19 and 4.20 can be combined with the link value probabilities from Table 4.21 as illustrated by Figure 4.14. This figure illustrates the glance proportions (using circles) and glance link probabilities (using arrows) between glance locations for 120 slow lead vehicle lane changes. Proportions in the circles represent the probability of at least one glance to that location while link probabilities represent the probability of a glance transition between two specific glance locations. In both cases values are for latency.

Two of the most likely glance locations were forward (0.99) and rearview mirror (0.46) with a link probability between these two locations of 0.30, a pattern similar to that reported by Tijerina et al. (1997) and Lee, Olsen, and Wierwille (2003). Also noteworthy was the link between forward (0.99) and left mirror (0.50) with a link probability of 0.27.

* In this table and the following tables, link probabilities that do not round to 0.01 or larger are not shown. Due to rounding, in some cases the total of the probabilities is slightly greater than or less than 1.0.

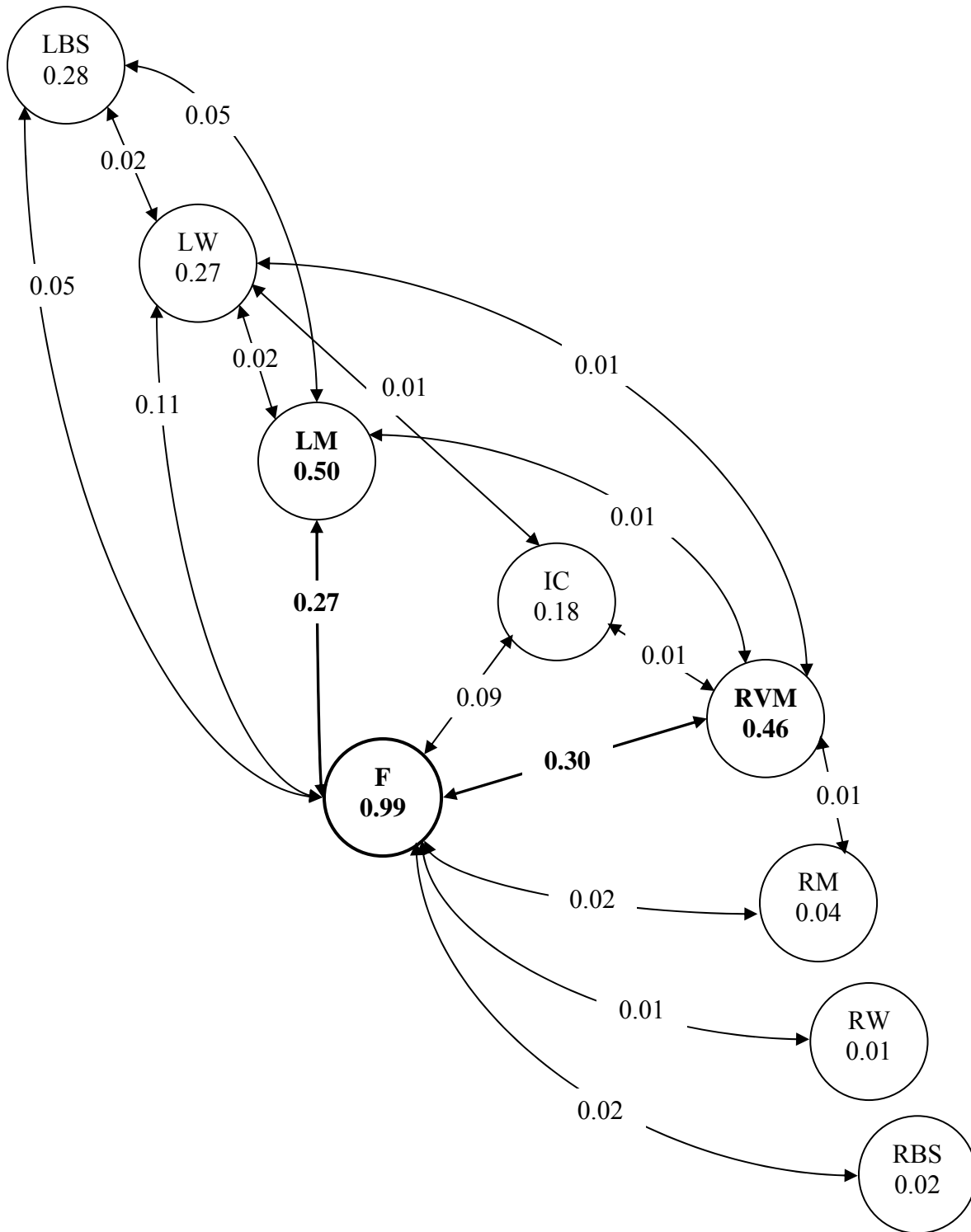


Figure 4.14. Glance Proportions (circles) and Link Probabilities (arrows) for the Sample of Slow Lead Vehicle Lane Changes (N = 120).

Baseline Events

Data for baseline events were analyzed in a similar manner as the lane change events. The proportion of glances to a particular location was evaluated; the highest proportion was also associated with glancing forward (first column of Table 4.22) with at least one glance to the forward view for 100% of the baseline events. For glance duration and the number of glances, each segment was analyzed in full since the eye glance analysis was relatively easy to perform (as compared to the larger set of, more glance-intensive lane change events). The mean analyzed duration was 20.1 s per baseline event (10 s event plus the 10 s prior to the event).

Number of Glances. There were a total of 330 glances across the 40 baseline events, with a mean of 8.3 glances per baseline event. The highest mean number of glances was 4.5 to the forward location (180 glances divided by 40 baseline events). The percent of total glances for the forward glance location was 54.6% (180 glances divided by 330 glances). Out of 40 baseline events, all of them had at least one glance to the forward view. Relatively large proportions of glances were allocated for glances to the rearview mirror and the instrument cluster as well. Table 4.22 illustrates the number of glances statistics for the baseline events.

Table 4.22: Number of Glances Statistics for the Baseline Events, All Glance Locations for Entire Event (40 events).

Glance location	Glance proportion*	Events w/ at least 1 glance	Mean Number Glances/Event	Total Number of Glances	Percent of Total number of Glances
F	1.00	40	4.50	180	54.6%
RVM	0.23	9	1.28	51	15.5%
LM	0.10	4	0.60	24	7.3%
LW	0.08	3	0.25	10	3.0%
LBS	0.03	1	0.03	1	0.3%
IC	0.25	10	1.20	48	14.6%
RM	0.05	2	0.05	2	0.6%
RW	0.00	0	0.03	1	0.30%
RBS	0.00	0	0.00	0	0.00%
OINT	0.05	2	0.33	13	3.94%
IND	0.00	0	0.00	0	0.00%
All events	1.00	40	8.25	330	100.00%

*Only analyzed during lane change latency.

Glance Duration. The total duration of glances combined was 804 s across the 40 baseline segments, with an overall mean glance duration of 20.1 s. Glances to the forward view had the highest mean glance duration per event with 17.3 s, as well as the highest mean single glance duration of 4.02 s per event. The percent of glance duration was 85.9% for forward (690.6 s/804.0 s), 4.7% for rearview mirror, 4.0% for instrument cluster, 2.1% for left mirror, and 1.5% for left window. Table 4.23 illustrates the glance duration statistics for the baseline events. These findings replicate those reported by Recarte and Nunes (2000) who reported that the percentage of fixations to the dashboard (i.e., instrument cluster) during ordinary driving was 4.0%, and that

glances to the dashboard are twice as likely as glances to the left mirror. The present results also provide general support for those reported by Zheng, McConkie, and Tai (2003) who found that drivers spent 73% of their time looking forward, 13% of glances toward the speedometer (i.e., instrument cluster), and 4.2% of the time was spent looking at the rearview mirror (note that Zheng et al., acknowledged that the percentage of glances to the speedometer was likely influenced by the need to look at task instructions).

Table 4.23: Glance Duration Statistics for the Baseline Events, All Glance Locations for Entire Event (40 events).

Glance location	Mean Glance Duration/Event (sec)	Total glance duration	% of glance duration	Mean single glance Duration (duration/# glances) (sec)
F	17.27	690.60	85.9%	4.02
RVM	0.94	37.60	4.7%	0.74
LM	0.43	17.20	2.1%	0.72
LW	0.29	11.70	1.5%	1.17
LBS	0.01	0.50	0.1%	0.50
IC	0.81	32.40	4.0%	0.68
RM	0.05	1.90	0.2%	0.95
RW	0.01	0.50	0.1%	0.50
RBS	0.00	0.00	0.0%	N/A
OINT	0.29	11.60	1.4%	0.89
IND	0.00	0.00	0.0%	N/A
All events	20.10	804.00	100.00%	2.44

Glance Link Analysis. The probability of a glance transition between two specific glance locations was also analyzed for the baseline data, as presented in Table 4.24. This glance link analysis included all 20 s of available data, as opposed to just the latency (4.6 s) for the lane changes.

Table 4.24: Link Probabilities between Eye Glance Locations for Baseline Events (N = 40).

	LW	LM	F	RVM	RM	RW	RBS	IC	OINT
LBS									
LW			0.04						
LM			0.14						
F				0.36	0.02			0.38	0.04
RVM									

The glance proportions from Tables 4.22 and 4.23 were combined with the link value probabilities from Table 4.24 as illustrated by Figure 4.15. This figure illustrates the glance proportions (using circles) and glance link probabilities (using arrows) between glance locations for the 40 baseline events. As a reminder, proportions in the circles represent the probability of

least one glance to that location while link probabilities represent the probability of a glance transition between two specific glance locations.

The most likely glance locations were forward (1.0), instrument cluster (0.25) and rearview mirror (0.23). The two strongest link probabilities were between forward and rearview mirror with 0.36, and between forward and instrument cluster with 0.38.

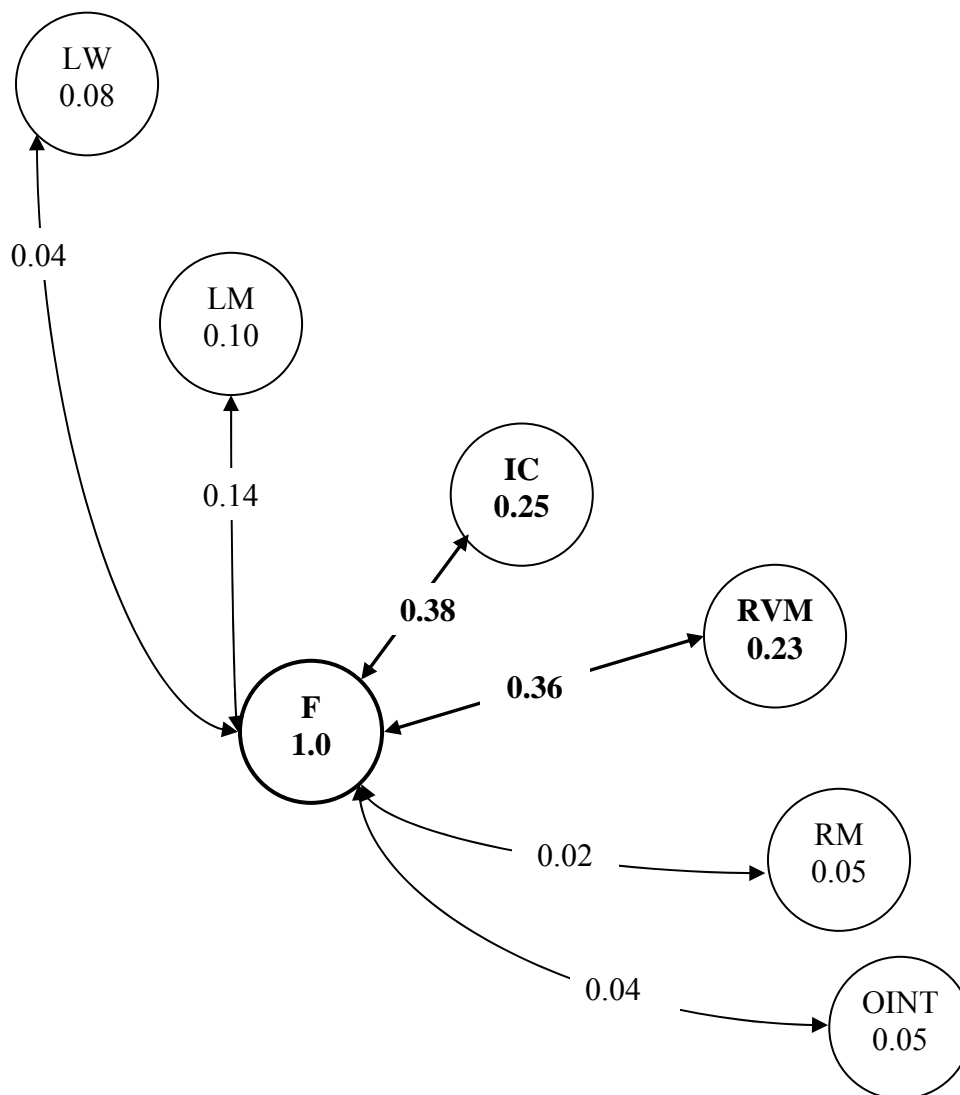


Figure 4.15. Glance Proportions (circles) and Link Probabilities (arrows) for the Sample of Baseline Events (N = 40).

Comparing Lane Changes and Baseline Events

Comparisons were made between differences for lane changes and baseline events. Comparisons were made among the glance probabilities, percent of total glances, and percent of glance duration as described. Table 4.25 lists the glance proportions for each location for lane changes and baseline events. The factor column indicates the multiplier by which the lane change glance was predominant. Values > 1 indicate that a higher proportion of glances were observed for lane changes and values < 1 indicate that a higher proportion of glances were observed for baseline events. For example, a 1.2 indicates that lane change glances to that location dominate over the baseline glances by a factor of 1.2. As a reminder:

Glance proportion is the proportion of time that at least one glance occurred to a particular location during the period analyzed (i.e., lane change latency);

The *percent of total glances* is the number of glances to a particular location divided by glances to any location during the event;

The *percent of glance duration* is the time looking at a location divided by total time of the event.

Forward glances were predominant in both conditions. During baseline events it appears the percent of total glances (number of glances forward divided by glances to any location during the event) was slightly higher with 54.6% vs. 50.6% for lane changes. In addition, the percent of glance duration looking forward (time looking forward divided by total time of event) was higher for baseline with 85.9% vs. 69.2% for lane changes.

For rearview mirror glances, glance probability (likelihood of at least 1 glance to a location during the event) was twice as high (0.46) for lane changes as opposed to baseline events (0.23). During baseline events it appears the percent of total glances was slightly higher with 15.5% vs. 14.0% for lane changes; however, the percent of glance duration looking in the rearview mirror was 8.3% for lane changes and only 4.7% for baseline events.

Table 4.25: Lane Change and Baseline Glance Proportions and Multiplier Factor by Which Lane Change Glances were Predominant.

Location	Lane Changes	Baseline Events	Factor
F	0.99	1.00	0.99
RVM	0.46	0.23	2.00
LM	0.50	0.10	5.00
LW	0.27	0.08	3.38
LBS	0.28	0	NA
IC	0.18	0.25	0.72
RM	0.04	0.05	0.80
RW	0.01	0	NA
RBS	0.02	0.05	0.40
OINT	0.01	0.05	0.20
IND	0.01	0	NA

Even more pronounced differences appear when viewing the left mirror, left window, and left blind spot, as one might expect when making a lane change to the left. Glances to these locations are fairly rare for baseline driving events, as shown by the glance proportions (0.10, 0.08 and 0.00 for left mirror, left window, and left blind spot respectively), whereas for lane changes, the pattern of left glances is unmistakable (0.50, 0.27, and 0.28, respectively). These same patterns can be found when viewing the percent of total glances and percent of glance duration as well. Most striking is the differences between baseline and lane change events for the left blind spot; the percent of total glances for lane changes is 6.8% vs. only 0.30% for baseline events, and the percent of glance duration is 4.1% for lane changes vs. 0.06% for baseline events.

Finally, note the difference between conditions for instrument cluster (speedometer) and other interior (e.g., radio, climate controls) glances. During baseline driving it substantially more glances are allocated toward these locations, as opposed to during lane changes. For example, for instrument cluster glances, the percent of total glances (number of glances to a location divided by glances to any location during the event) was 14.6% for baseline events vs. only 4.6% for lane change events. Likewise, for other interior glances, the percent of glance duration looking at other interior (time looking at other interior divided by total time of the event) was higher for baseline with 1.44% vs. 0.11% for lane changes. Finally, left or right blind spot glances were very rare for baseline driving.

Left and Right Lane Changes

Although most slow lead vehicle lane changes were to the left, separate analysis were conducted to characterize glance patterns for both left and right lane change. Inspection of the left lane changes reveals that the overall analysis and the left lane changes are essentially the same in terms of glance locations, proportion, and duration. By inspection of Tables 4.26 through 4.32, differences are apparent, particularly for glances to the side mirror and windows, and blind spots. Glances to the right are quite rare for left lane changes, and predominant for right lane changes. The tables are presented in pairs to facilitate making comparisons. The last table, Table 4.32 was included to show previous findings for right lane changes (Lee, Olsen & Wierwille, 2003). Figures 4.16 and 4.17 illustrate the glance proportions (using circles) and glance link probabilities (using arrows) between glance locations for both left and right slow lead vehicle lane changes, taken from the sample. Notice the emphasis of left glance for left lane changes and right glances for right lane changes. In addition, the rearview mirror is accessed frequently for lane changes in either direction.

Table 4.26: Number of Glances Statistics for the Sample of LEFT Lane Changes, All Glance Locations for the 3 Seconds Prior to t_0 (113 events).

Glance location	Glance proportion during latency	Events w/ at least 1 glance	Mean Number Glances/ Event	Total Number of glances	Percent of Total number of Glances
F	0.99	112	2.26	215	49.7%
RVM	0.46	52	0.65	73	14.2%
LM	0.53	60	0.70	79	15.4%
LW	0.28	32	0.35	40	7.8%
LBS	0.30	34	0.33	37	7.2%
IC	0.19	21	0.21	24	4.7%
RM	0.03	3	0.03	3	0.6%
RW	0.00	0	0.00	0	0.0%
RBS	0.00	0	0.00	0	0.0%
OINT	0.01	1	0.01	1	0.2%
IND	0.01	1	0.01	1	0.2%
All events	1.00	113	4.54	513	100.0%

Table 4.27: Number of Glances Statistics for the Sample of RIGHT Lane Changes, All Glance Locations for the 3 Seconds Prior to t_0 (7 events).

Glance location	Glance proportion during latency	Events w/ at least 1 glance	Mean Number Glances/ Event	Total Number of glances	Percent of Total number of Glances
F	1.00	7	2.86	17	64.5%
RVM	0.43	3	0.43	3	9.7%
LM	0.00	0	0.00	0	0.0%
LW	0.00	0	0.00	0	0.0%
LBS	0.00	0	0.00	0	0.0%
IC	0.14	1	0.14	1	3.2%
RM	0.29	2	0.29	2	6.5%
RW	0.14	1	0.29	0	6.5%
RBS	0.29	2	0.43	2	9.7%
OINT	0.00	0	0.00	0	0.0%
IND	0.00	0	0.00	0	0.0%
All events	1.00	7	4.43	31	100.0%

Table 4.28: Glance Duration Statistics for the Sample of LEFT Lane Changes, All Glance Locations for the 3 Seconds Prior to t_0 (113 events).

Glance location	Glance Duration/ Event (sec)	Total Glance Duration	Percent of Glance Duration	Mean Single Glance Duration (duration/# glances) (sec)
F	3.29	372.3	69.0%	1.46
RVM	0.40	44.9	8.3%	0.62
LM	0.46	52.3	9.7%	0.66
LW	0.24	27.0	5.0%	0.68
LBS	0.21	23.3	4.3%	0.63
IC	0.12	13.5	2.5%	0.56
RM	0.01	1.3	0.2%	0.43
RW	0.00	0.0	0.0%	N/A
RBS	0.00	0.0	0.0%	N/A
OINT	0.01	0.6	0.1%	0.60
IND	0.04	4.2	0.8%	4.20
All events	4.72	566.40	100.0%	1.04

Table 4.29: Glance Duration Statistics for the Sample of RIGHT Lane Changes, All Glance Locations for the 3 Seconds Prior to t_0 (7 events).

Glance location	Glance Duration/ Event (sec)	Total Glance Duration	Percent of Glance Duration	Mean Single Glance Duration (duration/# glances) (sec)
F	2.77	19.4	71.9%	0.97
RVM	0.26	1.8	6.7%	0.60
LM	0.00	0.0	0.0%	N/A
LW	0.00	0.0	0.0%	N/A
LBS	0.00	0.0	0.0%	N/A
IC	0.07	0.5	1.9%	0.50
RM	0.21	1.5	5.6%	0.75
RW	0.24	1.7	6.3%	0.85
RBS	0.30	0.7	7.8%	0.70
OINT	0.00	0.0	0.0%	N/A
IND	0.04	0.0	0.0%	N/A
All events	3.86	27.0	100.0%	0.87

Table 4.30: Link Probabilities between Eye Glance Locations for LEFT Slow Lead Vehicle Lane Changes (N = 113).*

	LW	LM	F	RVM	RM	RW	RBS	IC
LBS	0.02	0.05	0.05					
LW		0.02	0.11	0.01				0.01
LM			0.28	0.01				
F				0.31	0.01			0.09
RVM								0.01
RW								

Table 4.31: Link Probabilities between Eye Glance Locations for RIGHT Slow Lead Vehicle Lane Changes (N = 7).

	LW	LM	F	RVM	RM	RW	RBS	IC
LBS								
LW								
LM								
F				0.25	0.10	0.20	0.30	0.10
RVM					0.05			
RW								

Table 4.32: Link Probabilities between Eye Glance Locations for RIGHT Slow Lead Vehicle Lane Changes (N = 29) (replicated in part from Lee, Olsen, & Wierwille, 2003).

	LW	LM	F	RVM	RM	RW	RBS	IC
LBS								
LW								
LM			0.02					
F				0.60	0.12	0.07	0.12	0.03
RVM					0.03	0.02		
RW							0.02	

* In this table and the following tables, link probabilities that do not round to 0.01 or larger are not shown. Due to rounding, in some cases the total of the probabilities is slightly greater than or less than 1.0.

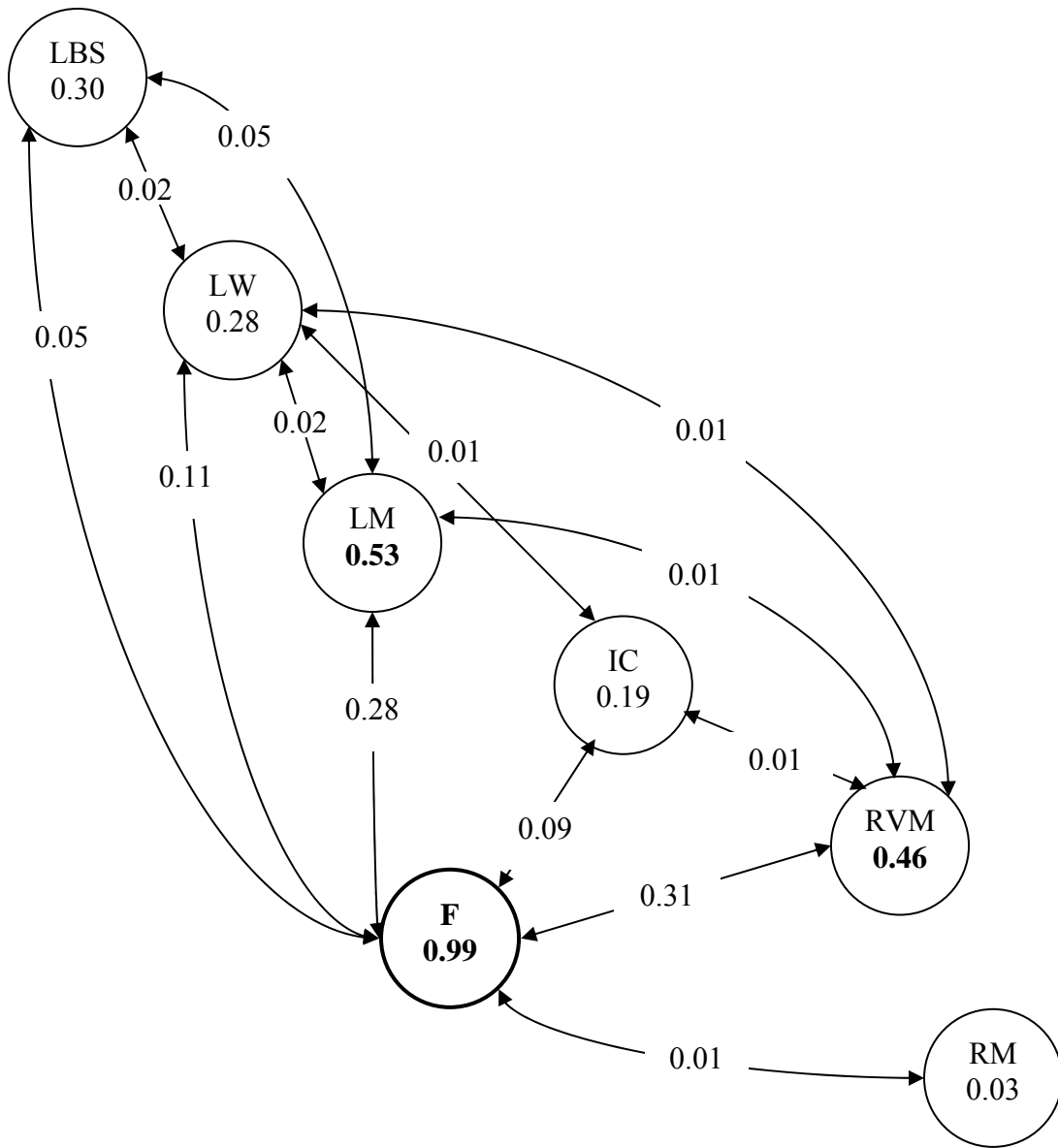


Figure 4.16. Glance Proportions (circles) and Link Probabilities (arrows) for Slow Lead Vehicle Lane Changes to the Left (N = 113 lane changes).

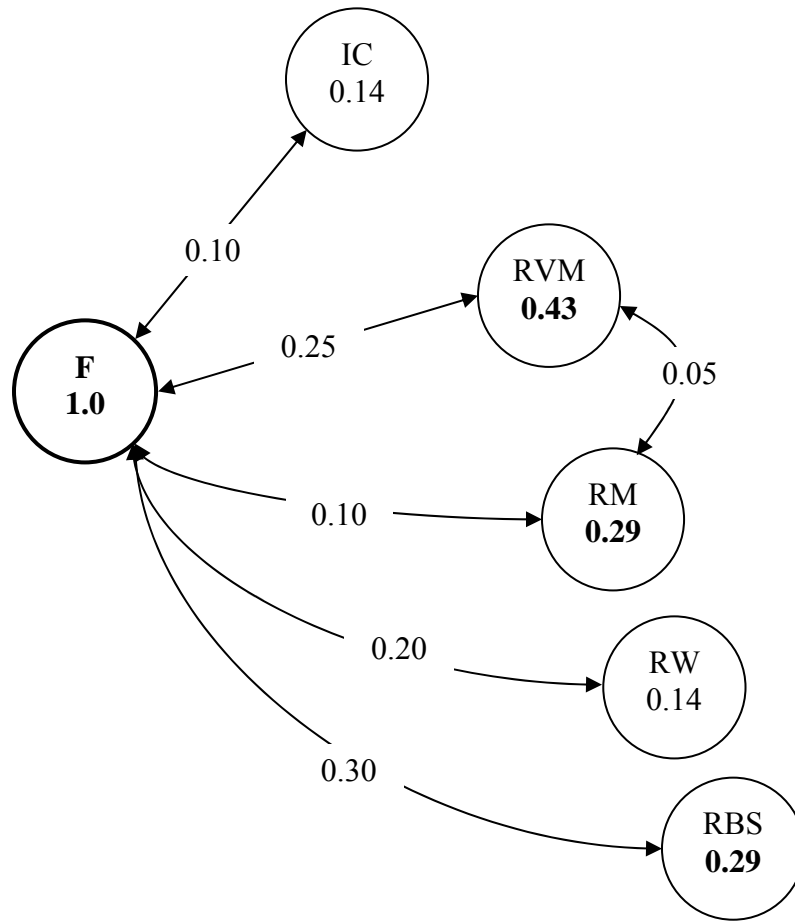


Figure 4.17: Glance Proportions (circles) and Link Probabilities (arrows) for Slow Lead Vehicle Lane Changes to the Right (N = 7 lane changes).

Predictive Model Development

A set of predictive logistic regression models were desired that used the data in which a slow vehicle was ahead and a vehicle was approaching in the rear adjacent lane. The purpose of these models was to discriminate between lane changes and straight-ahead (baseline) driving. Such models, although based largely on static data, could then serve as the basis of enhanced models that use dynamic data to predict when the lane change will begin, and when, if desired, a lane change crash avoidance system (LCAS) alert should be issued. These models would be relevant for lane changes in which a slow vehicle is ahead and a vehicle is approaching in the rear adjacent lane, and used various data such as velocity, range and TTC to relevant vehicles, and turn signal data. Glance location data was also included to enhance the models' ability to distinguish lane changes from baseline driving events, assuming such data could be available in the near future. After presenting these models, a brief discussion will follow regarding what other variables would be useful to improve these models. For example, having lane position data may strengthen the model's predictive power (e.g., using computer vision for lane tracking) as will likely be available in future automotive systems.

Logistic Regression

In logistic regression, the dependent variable is a dichotomous variable assigned the values of 0 (for baseline event) or 1 (for a lane change). The goal of using logistic regression for this research was to estimate the probability that a participant will change lanes, given certain values of the independent variables, such as velocity, range, and TTC to relevant vehicles. Ordinary linear regression (OLR) is not appropriate in this scenario since OLR assumes a continuous measurement response variable (not dichotomous) and the estimated response from OLR is not confined to be between 0 and 1, as required for a probability.

Assessing Fit of the Logistic Regression Models

To assess each model, the average fraction correctly classified for fit (AFCCF) is used. The AFCCF is a measure of the logistic regression model's ability to match the existing data and can be used in a manner similar to the R^2 statistic in OLR to compare several competing models (along with other performance statistics including the probability values for each regressor entered into the model, the probability value for the overall model, as well as non-statistical criteria such as the relative "expense" of acquiring particular regressors).

With OLR, all other things being equal, an R^2 with a relatively high value (i.e., close to 1) represents a better model (more variance is accounted for). AFCCF is similar in that higher values indicate a closer match between the model and the data. That is, an AFCCF that is closer to 1 reflects better agreement between the model and the data than an AFCCF that is closer to 0; an AFCCF = 1 indicates a perfect agreement between the model and the data (i.e., if the observed response is a 1, the model's estimated probability is also a 1, and if the observed response is a 0, the model's estimated probability is a 0 as well).

The AFCCF term was coined by Dr. Jeffrey Birch, a Professor of Statistics at Virginia Polytechnic Institute and State University (J. Birch, personal communication, 24 July 2003); however, at least one established statistical package (i.e., SYSTAT) produces an equivalent value. Likewise, SAS outputs FCC (under the ctable option), but FCC requires a cutoff value (e.g., 0.50) that is used to turn an estimated probability into a 0 or 1 response, and this cutoff is

subjectively determined by the user. This results in a possible variety of cutoffs, if selected by different users, thereby resulting in different values for the FCC. The AFCCF avoids this problem by not requiring a cutoff.

SAS output could be used to calculate AFCCF. This is accomplished by using the formula:

$$AFCCF = \frac{\sum_{i=1}^n y_i \hat{P}_i + \sum_{i=1}^n (1 - y_i)(1 - \hat{P}_i)}{n}$$

where,

y_i indicates the result is a lane change (1 for lane change)

\hat{P}_i indicates the estimated probability value of a lane change

$1 - y_i$ indicates the result is a baseline event (0 for baseline)

$1 - \hat{P}_i$ indicates the estimated probability value of a baseline event

n indicates the number of observations

So,

$\sum_{i=1}^n y_i \hat{P}_i$ is the sum of all y_i s times their respective estimated probabilities associated with a lane change (all y_i s associated with a baseline event are 0).

and

$\sum_{i=1}^n (1 - y_i)(1 - \hat{P}_i)$ is the sum of all $1 - y_i$ s times their respective estimated probabilities associated with baseline events (all $1 - y_i$ s associated with making a lane change are 0).

Determining Regressors

Step-wise regression techniques were used to determine which regressors were relevant for developing predictive models. Two categories of stepwise-type procedure exist, including forward selection and backward elimination (Montgomery, Peck, & Vining, 2001). The forward selection procedure uses the correlation value for a particular response variable to select regressors one at a time. The first regressor selected for the model has the largest correlation value; the second regressor is chosen to give the best fit to the data with 2 variables, given that the first regressor is included, and so on until the combined F statistic is below a preselected F value required for a regressor to enter the model. In other words, regressors are added until adding the next regressor does not improve the model significantly. In a similar manner, the backward elimination procedure starts by including *all* available regressors and then removing regressors until the best model is identified. Although forward selection and backward elimination procedures were used, the forward selection procedure identified six candidate models.

Forward selection and backward elimination procedures were used in the SAS statistical package to identify six candidate models. To identify these models, analyses were run based on the variables listed in Table 4.33. Each value was collected at, or relative to, lane change initiation (t_0). Note: SV = Subject (experimental) Vehicle; POV = Principal Other Vehicle.

Table 4.33: Regressor Type, Regressors, and Definitions as Used for the Logistic Regressions.

Regressor Type	Regressor	Definition
Vehicle	VehSpeed	Vehicle Velocity of SV at t_0
	Steer	Steering Position at t_0
	LatAccel	Lateral Acceleration (gs) at t_0 (negative indicates moving right)
	Brake	Brake Pedal Activation (yes or no) at t_0
	TTC1	Time to collision from SV to lead POV ahead
	TTC2	Time to collision from POV in the left rear adjacent lane to SV
	Dist1	Distance from SV to lead POV ahead
	Dist2	Distance from POV in left rear adjacent lane to SV
Signal	Sig_on	Turn Signal on or off? - A discrete response (yes or no)
	Sig_timing	Turn Signal Timing (+ or - 0) relative to t_0 (negative indicates turn signal was activated before t_0)
Glance	RVM	Rear View Mirror glance at t_0 (yes or no)
	LBS	Left Blind Spot glance at t_0 (yes or no)
	LM	Left Mirror glance at t_0 (yes or no)
	RM	Right Mirror glance at t_0 (yes or no)
	LW	Left Window glance at t_0 (yes or no)
	InstrCls	Instrument Cluster glance at t_0 (yes or no)

A series of models was analyzed including various combinations. Initially, models were analyzed in terms of each severity level as compared to the baseline group. For example, all the lane changes rated with severity = 1 were compared to the 40 baseline events. Then, all the lane changes rated ≤ 2 severity ≤ 4 were compared to the 40 baseline events and so on. Finally, all 120 lane changes were compared to the 40 baseline events. Results indicated that comparing the 120 lane changes to the 40 baseline events resulted in good models overall, in terms of AFCCF, sensitivity, and specificity values, as well as in terms of being practical; the group of 120 lane changes had lane changes representing all levels of severity (and urgency) and therefore, was very representative of a large range of maneuvers, as compared, for example, to the case when only the lane changes rated highest in severity were rated to the baseline events. In addition, the initial models used substitute values for missing data (see next section). These values were estimated to improve the models. Numerous values were experimented with to find reasonable substitute values. For example, initially, 100 s was used for TTC and 400 feet was used for distance as substitute; however these values seemed to be too extreme and produced models that were not as powerful, as when more conservative, more realistic values were used. (i.e., 61 s and 300 feet respectively).

Following the advice of Chovan et al. (1994, p. 7), “simple lane change models should be a first priority.” Adhering to this advice, the first model was the vehicle model, which included all of the vehicle regressors (VehSpeed, Steer, LatAccel, Brake, TTC1, TTC2, Dist1, and Dist2). The purpose of having a model that did not include the signal data was due to the fact that many people did not (and do not) use turn signals prior to performing a lane change. Mirror data was not included in this model because it is relatively expensive to acquire these data. The vehicle model took into account data that were either based on the SV itself (e.g., velocity), or based on the relationship between the SV and the POV (e.g., TTC derived from radar data).

Of all the potential regressors, only the regressors Dist1, TTC1, and Dist2 were entered into the vehicle model using forward selection, resulting in the following:

$$\hat{y} = 8.930 - 0.118 * TTC1 - 0.014 * Dist1 - 0.008 * Dist2$$

For this case:

$$\sum_{i=1}^n y_i \hat{P}_i = 110.899,$$

$$\sum_{i=1}^n (1 - y_i)(1 - \hat{P}_i) = 30.899,$$

$n = 160$ (120 lane changes and 40 baseline events)

$$so \text{ AFCCF} = \frac{110.899 + 30.899}{160} = \frac{141.798}{160} = 0.886,$$

indicating that this logistic regression model performs relatively well in its ability to match with the existing data (i.e., the AFCCF is close to 1).

Likewise, both average sensitivity and average specificity of the model can be calculated, where the closer the value is to 1, the better. To do this, the following formulas are used:

$$\text{Sensitivity} = \frac{\sum_{i=1}^n y_i \hat{P}_i}{\sum_{i=1}^n y_i} = \frac{110.899}{120} = 0.924, \text{ the probability of correctly classifying a lane}$$

change, when it is indeed a lane change

and

$$\text{Specificity} = \frac{\sum_{i=1}^n (1 - y_i)(1 - \hat{P}_i)}{\sum_{i=1}^n (1 - y_i)} = \frac{30.899}{40} = 0.772, \text{ the probability of correctly classifying a}$$

baseline event, when it is indeed a baseline event.

A typical classification table associated with these values of sensitivity and specificity might be presented as shown in Table 4.34.

Table 4.34: Classification Table for the Logistic Regression Vehicle Model.

		Fits		TOTAL
		1 (lane change)	0 (baseline)	
Actual	1 (lane change)	111	9	120
	0 (baseline)	9	31	40
TOTAL		120	40	160

Here it can be seen that the number of correctly classified lane changes is 111/120 (0.924), the number of correctly classified baseline events is 31/40 (0.772), and the overall fit of correctly classified events is 142/160 (0.886).

A similar procedure was followed resulting in a total of six candidate models. The vehicle + glance model had the vehicle and the glance regressor entered into model, including the left mirror and left window glance data. As a result, the AFCCF value of 0.943, as well as the sensitivity and specificity values increased. With the addition of the glance data, the predictive strength of the model was increased substantially.

It was anticipated that having turn signal data would aid in the ability of the logistic regression model to discriminate between baseline events and lane changes. However, since not all drivers use turn signals when making lane changes, models both with and without turn signal data were desired. Note that both turn signal timing data and binary (on/off) signal data were included. Binary turn signal data indicated if the turn signal was on or off at anytime prior to or after the start of the lane change. For the vehicle + signal model, a larger set of vehicle regressors, as well as the signal timing data, were entered into the model. Again, the AFCCF value of 0.956 as well as the sensitivity and specificity values increased, since more regressors were included in the model. Finally, the vehicle + glance + signal models were generated. With the turn signal timing data, the model included the instrument cluster (IC) glance, as illustrated by Tables 4.35 and Tables 4.37. See Appendix I for SAS code.

Table 4.35: Logistic Regression Regressors, Showing Vehicle, Glance, and Signal Regressors.

		Vehicle				Glance				Signal
Model	Intercept	Dist1	TTC1	Dist2	Brake	LM	LW	RVM	IC	Signal timing
v	8.930	-0.014	-0.118	-0.008						
v + g	12.616	-0.028	-0.214	-0.010		5.922	5.502			
v + s (on/off)	9.617	-0.011	-0.154	-0.012						15.823 (on/off)
v + s (timing)	10.057	-0.013	-0.221	-0.010	4.102					41.381 (timing)
v + g + s (on/off)	12.323	-0.025	-0.224	-0.011		5.907	5.036			13.282 (on/off)
v + g + s (timing)	24.385	-0.067	-0.727			11.579	26.945	4.931	-5.358	11.632 (timing)

Table 4.36: Logistic Regression Model Fit Including AFCCF, Sensitivity, and Specificity.

	Model Fit		
Model	AFCCF	Sensitiv.	Specific
v	0.885	0.923	0.770
v + g	0.943	0.962	0.887
v + s (on/off)	0.927	0.951	0.853
v + s (timing)	0.956	0.971	0.912
v + g + s (on/off)	0.956	0.971	0.912
v + g + s (timing)	0.986	0.991	0.974

Table 4.37: Logistic Regression Models and Model Formulas.

Model	Model Formula
Vehicle	$\hat{y} = 8.93 - 0.01 * Dist1 - 0.12 * TTC1 - 0.01 * Dist2$
Vehicle+Glance	$\hat{y} = 12.62 - 0.03 * Dist1 - 0.21 * TTC1 - 0.01 * Dist2 + 5.92 * LM + 5.50 * LW$
Vehicle+Signal (on/off)	$\hat{y} = 9.62 - 0.01 * Dist1 - 0.15 * TTC1 - 0.01 * Dist2 + 15.82 * Sig_on$
Vehicle+Signal (timing)	$\hat{y} = 10.06 - 0.01 * Dist1 - 0.22 * TTC1 - 0.01 * Dist2 + 4.10 * Brake + 41.38 * Sig_tim$
Vehicle+Glance+Signal (on/off)	$\hat{y} = 12.32 - 0.03 * Dist1 - 0.01 * Dist2 - 0.22 * TTC1 + 5.91 * LM + 5.04 * LW + 13.28 * Sig_on$
Vehicle+Glance+Signal (timing)	$\hat{y} = 24.39 - 0.07 * Dist1 - 0.73 * TTC1 + 11.58 * LM + 26.95 * LW + 4.93 * RVM - 5.36 * IC + 11.63 * Sig_tim$

Handling Missing Data

In most cases, the data used were straight forward. In all cases, each event had velocity, lateral acceleration, steering, braking, signal (if used), and glance data. In some cases values had to be entered for missing values to improve the performance of the model(s). Substitute values were selected that seemed to be reasonable and that improved the performance of each model. For cases in which a slow lead vehicle was ahead that was actually going *faster than* the SV, a value for TTC1 was not available (it would be infinity). For these cases, a value of 30 s was entered, indicating that the vehicle was not a threat to the SV. Out of a total of 160 cases this occurred 18 times (11.3%). During the 120 lane changes this occurred 15 times (12.5%) and during the 40 baseline events this occurred 3 times (7.5%). In other cases *there was no vehicle ahead*. This occurred only for the baseline events, and occurred in 11/40 (27.5%) of the cases. For these events both the Dist1 and the TTC1 values were filled. This was necessary due to limitations of the statistical package, which ignored any cases in which data were missing. For this reason, data were selected to represent a vehicle far in the distance that did not pose a threat to the vehicle. Distance was filled in with 300 feet, a value that corresponds to the outer range of the radar system. For TTC1, 61 s was chosen, indicating that if a vehicle had been present, it would not have been a threat to the SV.

A similar procedure was followed for vehicles in the rear adjacent (destination) lane at t_0 . For cases in which an approaching vehicle to the rear was actually going *slower than* the SV, a value for TTC2 was not available and would be infinity if calculated. For these cases, a value of 30 s was entered, indicating that the vehicle would not have been a threat to the SV. Out of a total of 160 cases this occurred 52 times (32.5%). During the 120 lane changes this occurred 43 times (35.8%) and during the 40 baseline events this occurred 9 times (22.5%). In other cases *there was no vehicle in the rear adjacent lane*. Out of a total of 160 cases, this occurred 47 (29.4%) times. During the 120 lane changes, this occurred 34 (28.3%) times and during the 40 baseline events this occurred 13 (32.5%) times. For these events both the Dist2 and the TTC2 values were filled in. Distance was filled in with 300 feet, a value that corresponds to the outer range of the radar system. For TTC2, 61 s was chosen, indicating that if a vehicle had been present, it would not have been a threat to the SV. Figures 4.18 and 4.19 illustrate the logic that was used for these decisions. Table 4.38 displays a summary of these data. Also note that the lane change analysis program assigned a maximum value of 60 s for cases in which the actual TTC was ≥ 60 s. The value of 61 s as a substitute value was selected to allow the experimenter to differentiate between the system maximum values and those substituted as described here by these logic diagrams. Finally, since side sensor data were not collected (no side radar sensors were used in this study), for values for distance to the rear, negative values indicated that a vehicle was present in the adjacent lane, but slightly forward of the rear bumper, beside the SV. Since exact values were not available, these data were estimated from watching video clips of the incidents. Also small positive values (e.g., < 20 feet) were estimate for distance in cases in which a vehicle was present next to the SV, but slightly behind it (e.g., in the blind spot) using the same method (i.e., viewing the video tapes).

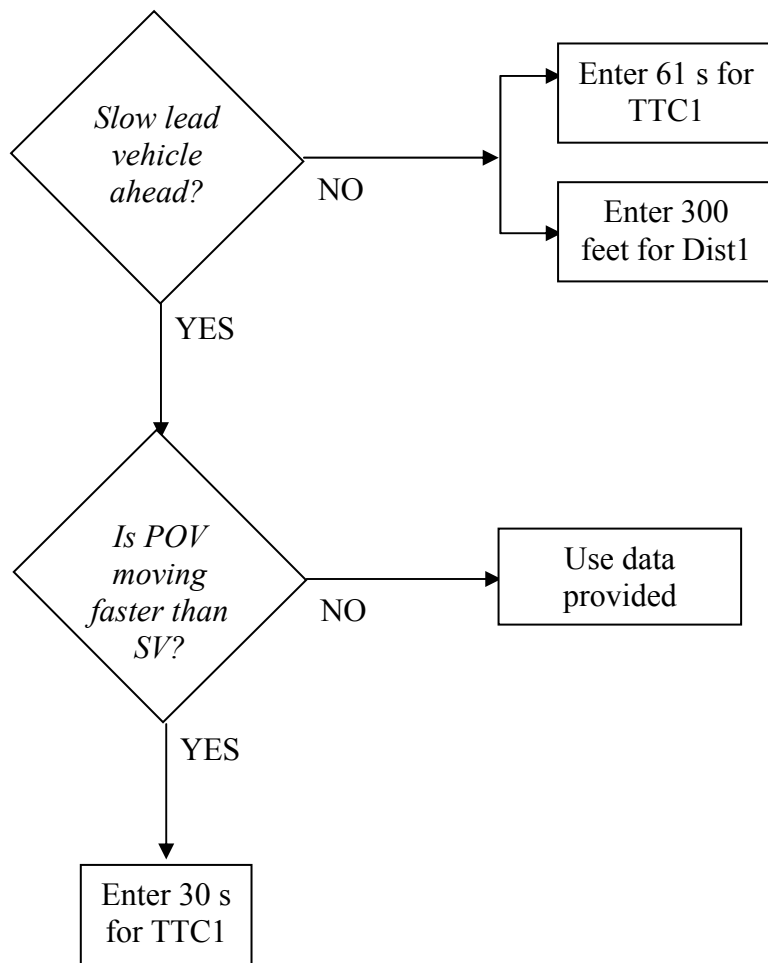


Figure 4.18. Logic Diagram for Handling Missing Data for Slow Lead Vehicles.

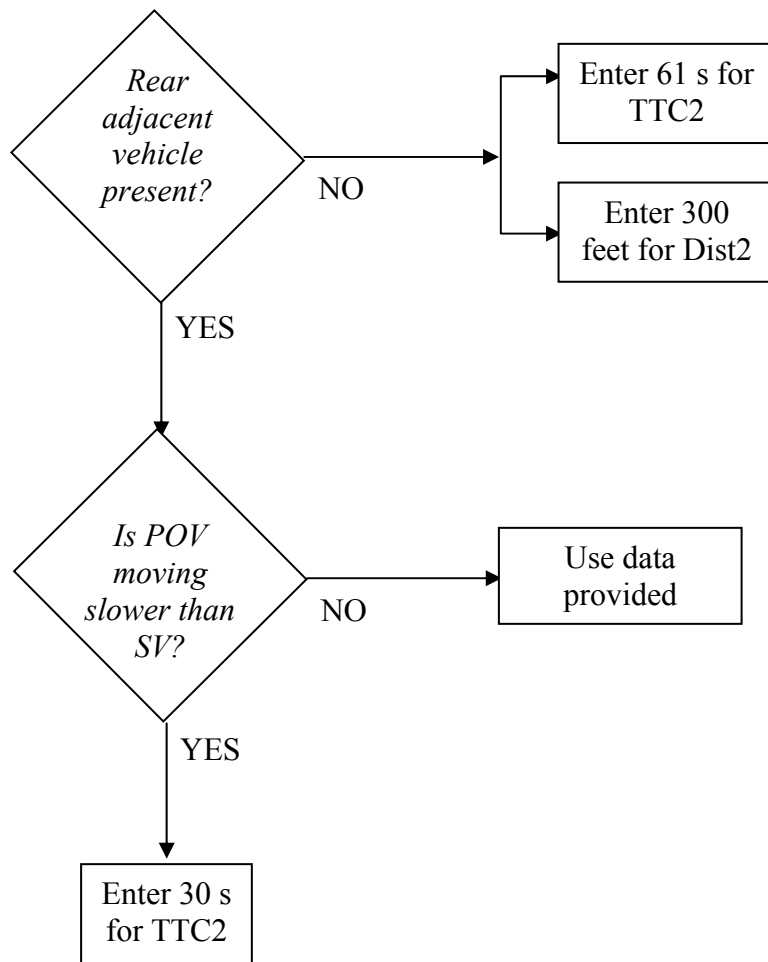


Figure 4.19. Logic Diagram for Handling Missing Data for Rear Adjacent Vehicles.

Table 4.38: Summary of Data Substituted for Missing Values.

Vehicle Relationship	Condition	Variable	Status	Substitute	N	% Total
POV ahead faster than SV	All 160	TTC1	infinite	30 s	18	11.3%
	LCs (120)				15	12.5%
	Baseline (40)				3	7.5%
No POV ahead of SV	Baseline (40)	TTC1	missing	61 s	11	27.5%
		Dist1	missing	300 feet	11	27.6%
POV in rear adjacent lane slower than SV	All 160	TTC2	infinite	30 s	52	32.5%
	LCs (120)				43	35.8%
	Baseline (40)				9	22.5%
No POV in rear adjacent lane	All 160	TTC1	missing	61 s	47	29.4%
	LCs (120)				34	28.3%
	Baseline (40)				13	32.5%
	All 160	Dist2	missing	300 feet	47	29.4%
	LCs (120)				34	28.3%
	Baseline (40)				13	32.5%

Transforming Turn Signal Data

As previously mentioned, turn signal timing data was reported in terms of the amount of time in seconds that the turn signal was activated before or after t_0 . Therefore, a mixture of positive and negative values was observed with a minimum value of -5.6 and a maximum of 1.9. These data were transformed to positive values by adding 5.7 to all cases in which a signal was used, so the minimum was 0.1 and the maximum was 7.6. For each of these cases, this new sum was then subtracted from 7.7 for all cells so that values would be transformed and be positive; the closer the value to zero, the later the turn signal was activated. For example, if a signal was activated 1.5 seconds after t_0 , it would be transformed by adding 5.7 to 1.5 for a total of 7.2. This value would then be subtracted from 7.7 to get 0.5. The higher the value, the earlier the turn signal was activated (i.e., that is “better” because it gives more time for the system to determine if the signal is on before the lane change starts). All cases in which no signal was used remained zero. This method allowed turn signal data to be more useful for modeling purposes. In addition, as previously mentioned, models were derived using the binary (on/off) turn signal data as well.

Model Validation

In an attempt to validate the models, another sample of data was extracted from the data archive. A total of 301 slow lead vehicle lane changes had been previously analyzed as part of the larger project (Lee, Olsen & Wierwille, 2003). The sample of 120 was chosen from this set. For the original analyses, the sample of 120 lane changes was reviewed several times, case by case. This was very time-intensive; however, it was necessary to verify that the vehicle detected in the forward view was in fact the slow lead vehicle in question. A similar process was completed for vehicles in the rear adjacent lane. For cases in which vehicles were present in the adjacent lane at t_0 but were not, however, within radar range since they were very close to the SV, distance and TTC values were estimated by viewing the video for each case. For the validation sample of lane changes, these same procedures were not followed.

In choosing the validation sample, it was determined that 181 available events remained from the total sub-set of 301 previously analyzed lane changes. This sub-set was reviewed and only those events in which a vehicle was present in the front and in the rear of the SV were selected. This was performed in lieu of the case-by-case review performed for the sample of 120 used in the first analysis. A total of 85 lane changes met these criteria. For cases in which more than one vehicle was detected by a radar unit, it was assumed that the closest vehicle was the POV. That is, the slow lead vehicle was assumed to be the forward vehicle closest to the SV, and the rear adjacent vehicle was assumed to be the vehicle detected in either the left or right rear radar at t_0 . Finally, signal data only consisted of binary (on/off) data *taken at t_0* . For the original analysis, each event was reviewed to determine the timing of the turn signal activation. The values for the binary turn signal data originally reported by the lane change analysis program were then modified to account for cases in which a signal was activated *taken after t_0* . However, this same procedure was not performed for the validation set of data: only the original turn signal data were used (i.e., binary data taken at t_0). These assumptions were made in an attempt to select a validation sample in a timely manner, which could be used as a reasonable set for model validation purposes.

Given these limitations, the models performed relatively well with the validation set of data, although the AFCCF, sensitivity, and specificity values were slightly lower for the validation set. Regardless, the best model was the vehicle + glance + signal model, due to its ability to use numerous data to distinguish lane changes from baseline driving events. One noticeable difference was that for the validation set, the vehicle + glance model actually performed better than the vehicle + glance + signal model. This was probably because the turn signal data were only taken at t_0 , for the validation set of 85 lane changes, whereas the sample of 120 lane changes included binary data that had been modified; each event had been analyzed to determine if in fact, the turn signal had been activated at any time during the lane change, and the overall percentage of use for the sample (64%) was higher than for the validation sample (54%). Tables 4.39 through 4.41 illustrate the performance of the validation models.

Upon making comparisons between the sample set and the validation set of data, the addition of the turn signal data and the glance data do make the models better in terms of discriminating between lane change maneuvers and baseline driving events. It appears that the vehicle + signal model is the single best model because it could be implemented with relative ease. Based upon models generated from the sample data and the validation data, the AFCCF value is between 0.88 and 0.93 with sensitivity between 0.92 and 0.95, and specificity between 0.82 and 0.85. Thus, a model that includes data relevant to the slow lead and rear adjacent vehicle and the turn data is a good model.

Table 4.39: Logistic Regression Regressors, Showing Vehicle, Glance, and Signal Regressors for Validation Sample.

		Vehicle						Glance				Signal
Model	Intercept	Dist1	TTC1	Dist2	TTC2	Brake	LM	LW	RVM	IC	Signal timing	
v	8.417	-0.019	-0.082		-0.053							
v + g	8.517	-0.018	-0.151	-0.013			4.284	4.863	8.517			
v + s (on/off)	6.160	-0.022	-0.084								13.680 (on/off)	
v + g + s (on/off)	6.450	-0.024	-0.105			4.545	3.666				13.795 (on/off)	

Table 4.40: Logistic Regression Model Fit Including AFCCF, Sensitivity, and Specificity for Validation Sample.

	Model Fit		
Model	AFCCF	Sensitiv.	Specific
v	0.849	0.889	0.763
v + g	0.931	0.950	0.893
v + s (on/off)	0.884	0.915	0.819
v + g + s (on/off)	0.908	0.932	0.856

Table 4.41: Logistic Regression Models and Model Formulas for the Validation Sample.

Model	Model Formula
Vehicle	$\hat{y} = 8.42 - 0.02 * Dist1 - 0.08 * TTC1 - 0.05 * TTC2$
Vehicle+Glance	$\hat{y} = 8.52 - 0.02 * Dist1 - 0.15 * TTC1 - 0.01 * Dist2 + 4.28 * LM + 4.86 * LW + 8.52 * RVM$
Vehicle+Signal (timing)	$\hat{y} = 6.16 - 0.02 * Dist1 - 0.08 * TTC1 + 13.68 * Sig_on$
Vehicle+Glance+Signal (timing)	$\hat{y} = 6.45 - 0.02 * Dist1 - 0.11 * TTC1 + 4.55 * Brake + .367 * LM + 13.80 * Sig_on$

Descriptive Results of Dependent Variables

For the sake of completeness, Table J.1 through Table J.5 in Appendix J display all available data with descriptive results. Note that for Table J.2, brake data were not included. Brake data were reported in terms of the frequency of occurrence; for the sample of 120 lane changes, there were 5 cases in which the brake was activated at t_0 (4.2%), whereas for the baseline events, there was 1 case out of 40 (2.5%) in which the brake was activated. Vehicle speed, although not part of the models by itself, was of course required to calculate other parameters such as TTC. Neither steering nor lateral acceleration were shown to be valuable for the models because neither of these measures was sensitive enough for discriminating between lane changes and baseline events. Even the most extreme values could have been observed for other reasons including normal corrections to maintain lane position or due to changes in the road curvature.

Again for the sake of completeness, Table J.6 through Table J.10 display all available data with descriptive results for the validation data. For the validation sample of 85 lane changes, there were 5 cases in which the brake was activated at t_0 (5.9%). Inspection of these tables reveals that the validation sample, for the most part, displays similar characteristics as the sample of 120 lane changes. One exception is the severity rating, which is much higher for the validation sample. This was because lane changes were only selected that had a vehicle in both the front of the SV and in the rear adjacent lane, which tended to be cases rated high in severity. Nonetheless, the samples are equivalent in most other regards.

CHAPTER 5: CONCLUSION AND DISCUSSION

This dissertation has focused on characterizing lane changes, creating predictive models, and providing design guidance for system design. With proper testing and implementation, the findings presented provide data that may be used as the basis of well designed CAS. In the future, it may be possible to implement control intervention systems or fully automatic controls (Chovan et al., 1994). However, it has not been proposed that automatic vehicle control systems be implemented based on the present investigation. The timing and severity of potential crashes may warrant vehicle-controlled systems if a crash is determined to be otherwise unavoidable. However, the level of control would need to be evaluated and tested based on the driving scenario. That said, the lane change CAS (LCAS) is solely meant to be an alert or warning system to aid the driver in making decisions about whether or not to initiate a lane change. This system would include both a “presence detector” that detects the presence of a vehicle in the rear fast approach zone (30 to 162 feet behind the SV) or the proximity zone (4 feet in front of the SV to 30 feet behind it), and a warning system that warns the driver when a vehicle is detected and it is predicted that a lane change is about to occur. Such systems are intended to assist drivers to increase and maintain awareness, avoid potential hazards, and maintain safe driving. The findings presented herein support the development of such systems.

Crash avoidance systems are intended to provide messages in a timely manner so that the driver has time to perceive, understand, and react appropriately. Due to the complexities inherent in developing a CAS, the timing, format, exact location, etc. would need to be created, evaluated, and tested as well before the implementation of LCAS into the marketplace. Such testing would need to be conducted involving a variety of drivers, situations, and vehicles. It would need to account for the possibility of driver adaptation, in which “normal” behaviors are modified in response to the introduction of an additional driving device.

The present experiment revealed that participants drove a total of 23,949 miles, with an average of 37.4 miles per commute. A total of 3,227 slow lead vehicle lane changes were completed with an average of 7.7 miles between lane changes (0.13 lane changes/mile). Overall, the mean lane change duration time was 6.3 s and the large majority (92%) of lane changes were to the left.

In making comparisons between the large set of 3,227 slow lead vehicle lane changes and the sample of 120 lane changes, it was discovered that the sample was a good representation of the larger set. The sample, however, had mean severity and urgency ratings that were higher than the large set. Due to stratified sampling, the sample emphasized lane changes that were potentially more dangerous than the larger set of lane changes. The significance of this difference is two-fold. First, this verifies that the sample was representative of the riskiest maneuvers available to date. By including a variety of maneuvers ranging from “safe” to “risky” in the sample, the conclusions will represent realistic lane change cases. Second, recommendations and design guidelines based upon these analyses are likely to be practical and relevant not only to “average” lane changes but also to cases in which an alert is likely to be needed.

Route Differences

An examination of normalized data indicated that interstate drivers performed fewer slow lead vehicle lane changes per mile than did highway drivers. In addition, differences were revealed in terms of mean urgency ratings (related to the TTC to the slow vehicle ahead). The mean urgency rating of interstate lane changes was lower than the mean urgency rating for

highway lane changes. It is likely that highway drivers require more frequent lane changes, and that the average highway lane change is rated more highly because: 1) there is a higher likelihood that slower vehicles (e.g., tractors and farm vehicles) are encountered; 2) off ramps may be relatively short, causing traffic to slow or stop quickly, and on ramps provide less time for vehicles to reach highway speeds before entering; 3) highway routes typically include traffic signals, turn-outs, exits/entrances, which would also lead to a higher likelihood that vehicles ahead are slowing to turn or stop, as compared to the interstate; 4) there is a higher likelihood of exits to the left and right, whereas the freeway typically only has right exits. In other words, interstates are designed for smoother entering and exiting due to a high degree of access control, which leads to less variability in overall driving performance. In addition, interstates typically have better sight lines (i.e., the driver can see further) due to the use of wider lanes, large medians, and more prominent shoulders, often along less hilly or curvy routes. Finally, it is possible that performing lane changes on routes with relatively high traffic densities would be more difficult than on routes with low traffic densities. In fact, a report by the Virginia Department of Transportation (VDOT) revealed that the average annual daily traffic (AADT), a measure of traffic volume, was 24,000 for Interstate 81 and 12,000 for US Route 460 in Montgomery County, Virginia (VDOT, 2002). So it makes sense that fewer lane changes were observed on the Interstate, since the AADT was relatively high.

Usual Vehicle Differences

An examination of both the frequency and normalized data for usual vehicle (vehicle normally driven) revealed that people that usually drive SUVs performed fewer slow lead vehicle lane changes than sedan drivers. The reason that sedan drivers display more lane changes is somewhat perplexing; however, it is logical to conclude that drivers of sedans would tend to perform more lane changes because they are used to driving a vehicle that has a relatively high degree of maneuverability and control. Sports utility vehicle drivers are used to driving a larger, less maneuverable vehicle, and therefore may perform fewer lane changes per mile. Following this logic, the data support the notion that, *regardless of which experimental vehicle is driven*, sedan drivers (drivers who usually drive sedans) are more likely to make a lane change during their commute to work, as compared to an SUV driver.

Turn Signal Use

Findings from the present investigation address the issue of turn signal use for lane changing without the presence of an experimenter. Experimenter presence is likely to increase the compliance of turn signal use, as supported by previous findings that stated that turn signal use was between 85% and 92% (Hetrick, 1997; Tijerina et al., 1996). For the present investigation, the frequency and timing of turn signal use seemed to be representative of how drivers might use them under normal circumstances. Analysis of signal use revealed that turn signals were activated at t_0 41% to 54% of the time. These findings closely replicate those of Lee, Olsen, and Wierwille (2003), in which 500 lane changes were analyzed. They found that at t_0 turn signals were used in 44% of the slow lead vehicle cases. In fact, analysis of turn signal timing data revealed that turn signals were used 64% of the time when making a lane change. Turn signal activation was, on average, just prior to or very close to the lane change start (ranging from -5.6 s to 1.9 s), providing general support of previous findings reported by Hetrick (1997).

Results indicated that turn signals were used in all cases by 38% of drivers. Four drivers used turn signals infrequently (< 17% of the time), and over one-third of lane changes did not have a turn signal activated at all prior to or after the lane change was initiated. A portion of the lane changes in which signals were not used were lane changes where no other traffic was present; for 30% of the cases in which no turn signal was used, no other vehicles were behind or adjacent to the SV at the time when a turn signal might have been activated. Some drivers may rationalize that there is little need to use a signal if no other cars are present or if cars are present but not close to the vehicle.

Turn signal use is highest for lane changes rated low or moderate for urgency and moderate for severity; for the lane change cases that involve surrounding traffic, drivers are more likely to use a turn signal to indicate their intention. Further investigation revealed that other vehicles were nearby when the lane change was initiated for 70% of the cases in which a turn signal was not used. In fact, most of these cases involve other vehicles that were very close (i.e., < 80 feet) to the rear or front of the vehicle. Ironically, the results indicate that turn signals are least likely to be used for those cases rated high in terms of urgency and severity ratings. This may be due to lack of planning on the part of the driver, or perhaps was intentional on the driver's behalf. It is possible that some drivers believe that signaling before changing lanes encourages other drivers to speed up and close the gap so that the signaling vehicle cannot make the lane change.

Turn signal use may be low because the SV driver assumes that the driver of a vehicle in the adjacent lane is paying attention to the situation at hand. The SV driver may further assume that the other driver "knows" that the SV is going to change lanes in front of the adjacent vehicle. Another possible case is that of a large, slow semi-truck being the slow lead vehicle. In this case, the SV might assume that a vehicle to the rear also sees the semi-truck, and this "obvious" vehicle is going to be passed by the SV. If a SV driver assumes that the other driver is aware that the SV is nearby, then it is logical to assume that the SV driver may not bother to activate the turn signal, as illustrated by Figure 5.1. This series of assumptions is a loose interpretation of what Lee, Olsen, and Wierwille (2003) reported for passing maneuvers-- the reason that drivers may not use their turn signal during the *return portion* (moving back into the right lane after passing a driver) of a lane change may be because the driver of the slow lead vehicle that was just passed was aware that the SV was overtaking them.

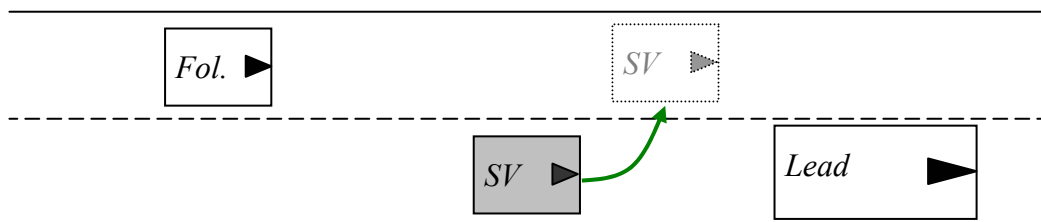


Figure 5.1. Theoretical Case in Which SV changes Lanes in Front of the Following Vehicle with no Turn Signal Activated.

On the other hand, drivers may not signal as a result of lack of training (signaling is not habitual for that driver) or possibly because of an equipment malfunction. Finally, turn signal use may be low overall because *drivers are unaware that another vehicle is nearby* when they initiate the lane change.

Application to Design

Turn signal use data are important for CAS designers who are designing systems that use turn signal data as an indicator of lane change intention. Many drivers use turn signals much of the time; however, use is not uniform within and between drivers. For this reason, it is recommended that CAS be designed to use turn signal data if available. This information should be incorporated into warning/alerting algorithms because, when used, signal use is a strong predictor of lane change likelihood. On the other hand, a system that relies on signal use either heavily or exclusively will not be sufficient for many drivers. It is feasible that a well-designed system may actually *increase* turn signal use. If a system rewarded the driver for using turn signals, usage would increase. For example, a system known as AutoVue issues an auditory warning in the form of a virtual rumble strip when the vehicle is near the lane border; the warning is designed to be disabled by the use of a turn signal, serving as an incentive to drivers to use their turn signals prior to initiating lane changes (Ledford, 2003). AutoVue systems are currently in use by Freightliner and International trucks in the U.S., as well as Mercedes and MAN trucks in Europe (C. L. Van Dan Elzen, personal communication, September 5, 2003). In another related application, Mazzae and Garrott (1995) recommend that the turn signals should be the stimulus for an auditory warning in side collision avoidance systems. That is, should a warning be warranted. Finally, future systems may include an enhanced turn signal-activated system that would engage a lane change only when conditions are safe. These systems might be based upon the currently used turn signal activators and would issue warnings as needed. In addition, visual displays might be an enhancement of current turn signal displays with various arrows, colors, sounds, or other displays.

As another example, future vehicles could include driving assessment modules that would periodically offer a driving skills assessment for the driver. Alternatively, it may be possible to collect data from drivers and provide feedback in real-time. Relevant and interesting data could be summarized and reported to the driver in a customized format; this data might include velocity, distance driven, gasoline consumption, following distance, rate of lane change/mile, turn signal usage, and “close-call” data. For turn signal data specifically, it may be possible to provide feedback to drivers about how to improve signal use. Specific messages such as “your current signal use rate is 73%” or “your mean following distance is 44 feet” might be issued, with a follow-up message such as, “it is recommended that signals be used earlier and that following distance be increased to maximize safety.” In the airline industry, “black box” technology has been used for years in airplanes to record pilot and vehicle behavior, and this has proved essential for accident reconstruction. Road Safety International revealed such a device for sale on September 8, 2003, as revealed at the 2003 National Safety Council conference in Chicago. Known as the RS-1000, this black box is an on-board computer that monitors speed, rpm, vehicle stops, idle time, daily distance, brakes, use of seatbelts, turn signals, etc. Warning tones and alarms alert the operator if the dynamic force at work on the vehicle exceeds recommendations, such as when a driver brakes too hard or turns a corner too fast (Oldenburg, 2003; Road Safety, 2002).

Another idea would take advantage of vehicle-to-vehicle or vehicle-to-infrastructure communications that are on the horizon. In the future, vehicles with crash avoidance and information systems will be able to “talk” to one another, allowing the sharing and verification of data. For example, Huang et al. (2001) describe a low-cost system based upon vehicle-to-vehicle communication so that potential hazards could be avoided. It is feasible that information could be exchanged with all surrounding vehicles with the same system. These systems could also

communicate with other devices such as “smart” traffic signals that could detect when a vehicle has a turn signal activated, allowing the driver to receive an appropriate “green turn arrow” in a timely manner. This would provide a reward to the driver who uses turn signals and offer another strategy for increasing turn signal use.

Eye Glance Analysis

Eye glance data were analyzed during latency for both the sample of 120 lane changes and the 40 baseline events. Results were reported for glance location probabilities, link value probabilities, and mean single glance times.

Analysis of the Sample

Analyses of the sample revealed that, for essentially every lane change (99%), there was at least one glance to the forward direction during latency. Forward glances also had the longest mean single glance time (1.4 s) and the highest mean glance duration (3.3 s) per event. This finding is not surprising, given that driving is primarily a visual forward tracking task even when lateral movement is being planned. During lane change latency, glances were also common to the rearview and left mirrors, as well as to the left side of the vehicle, including left window and left blind spot. This finding fits intuition, since, in preparation for a lane change to the left, most drivers would acquire information about the presence of vehicles in the left adjacent lane by scanning these positions. In fact, in looking at the left mirror, left window, and left blind spot in combination, at least one glance in one of these locations was found in 72% of the cases sampled. Thus, it appears that prior to making a left lane change, drivers do check to the left very often.

The highest link value (glance transition probability) was between the forward view and the rearview mirror, with high probabilities observed between the forward and left mirror locations. These findings replicate in large part those of Lee, Olsen, and Wierwille (2003), as expected. In addition, the general pattern of results reported by Tijerina et al. (1997) was also supported. For example, the probability of glancing to the rearview mirror was 0.46, and the probability of glancing to the left mirror was 0.50 (i.e., the probability of glancing for these two locations was approximately the same).

Analyses were conducted separately for left and right lane changes. Although the occurrence of right lane changes was low, the pattern observed generally supported those previously reported by Lee, Olsen, and Wierwille (2003), as well as Tijerina et al. (1997). As one might expect, left lane changes had a predominance of glances to the left side prior to initiation, whereas right lane changes had a predominance of glances to the right. For left lane changes, most glances were made to the forward view, rearview mirror, and left mirror leading up to t_0 . Glances to the left window, left blind spot, and (to some extent) instrument cluster were common, with glances to the right side of the vehicle being very rare. For right lane changes, 100% of events had at least one glance to the forward view, with a large proportion of glances made to the rearview mirror, right mirror, and right blind spot. Glance patterns were very distinct from left lane changes, mainly because no glances were made to the left. Other distinctions included the finding that the right mirror was used for a large proportion of the glances (0.29); however, the right side mirror was used much less than was the left side mirror (0.53) for left lane changes. There were no left mirror, left window, or left blind spot glances observed for right lane changes.

Analysis of Baseline Events

For baseline events, analysis revealed that there was at least one glance to the forward direction for every lane change during the 20 s period. Forward glances also had the longest mean single glance time (4.02 s) and the highest mean glance duration (17.3 s) per event. Glances were also common to the rearview mirror and the instrument panel (e.g., speedometer), as well as to the left side of the vehicle (left mirror and left window). In looking at the left mirror, left window, and left blind spot in combination, there was at least one glance in one of these locations in during baseline driving. However, glances to these locations only occurred in 15% of the cases.

The highest link value (glance transition probability) was between the forward view and the instrument cluster, with high probabilities also observed between the forward view and rearview mirror. Glances to the instrument cluster and rearview mirror had a similar probability rate (0.25 and 0.23 respectively), as did glances to the left mirror and left window (0.10 and 0.08 respectively).

Comparisons Between the Sample and Baseline Events

Comparisons between the sample of lane changes and the baseline events indicate that, as expected, forward glances were predominant in both conditions, with more glances and time spent looking forward during baseline events. Large differences were observed in terms of glance patterns around the vehicle. For lane change events, the probability of a glance to the rearview mirror and the percent of glance durations was twice as high, as compared to baseline events.

Glance analysis for left mirror, left window, and left blind spot revealed large differences between lane change and baseline events. Glances to these locations are essential for left lane changes so that drivers can determine when it is safe to change lanes. However, for baseline events, glances to these locations are fairly rare, since most of the time is spent glancing forward to monitor vehicles ahead, toward the rearview mirror to monitor activity to the rear, or the instrument cluster to monitor vehicle status (e.g., speed).

Finally, glances toward the blind spot during lane changes in which a turn signal was used occurred only for 40% of the cases sampled. In addition, for 86% of the cases in which no signal was used, no blind spot glance was performed. The reasons that so few people check their blind spot when using their signal are unknown. It may be that drivers rely upon their memory, or it is possible that some drivers have neck dexterity problems and have trouble turning their neck. What is most likely is that drivers rely upon their mirrors and their memory of what is behind them, and the assumption that the situation to the rear and side had not recently changed (Tijerina et al., 1997). Finally, it is possible that some drivers have not been trained in the importance of checking their blind spot before performing a lane change.

Design Recommendations

The glance patterns of drivers need to be considered in making recommendations for CAS design. In conjunction with the analysis of glance patterns of drivers, a multitude of factors need to be considered when making design recommendations. This section outlines recommendations for warning levels, warning modalities, and display locations that simultaneously include a number of relevant considerations.

Warning Levels

Warning levels for lane changing would likely be modeled after the NHTSA rear-end algorithms (Brunson, Kyle, Phamdo, & Preziotti, 2002). The recommendation is for four warning levels that include: no alert, early, intermediate, and imminent. However, a modification of this paradigm should be used for an LCAS because lane changes and lateral movements occur quickly (i.e., the time from lane change initiation to the point at which the tire begins to cross the lane line is approximately two seconds), and drivers would have difficulty comprehending two or three alerts if they were issued within a very short period of time. For an LCAS, a “presence detection” indicator and an imminent alert are recommended.

As previously mentioned, an LCAS is intended to aid the driver in making decisions about whether or not to initiate a lane change. Prior to receiving a warning, a presence detection display would be used. This display would provide information about the presence of a vehicle in the rear adjacent lane (i.e., in the fast approach zone or proximity zone) anytime such a vehicle is detected. An imminent warning would only be issued when the system predicts that a lane change is about to occur and a vehicle is detected in the rear, adjacent zone. This would be considered an imminent warning because, if the present situation continues and no action is taken, a collision is imminent.

Display Modality

A review of the literature revealed that warning displays should be visual for the no-alert and early warnings (Mazzae & Garrott, 1995; Campbell, Carney, & Kantowitz, 1998). This supports the concept of a presence indicator in a visual format. Steady amber or red lights should be used for cautionary warnings (Campbell, Hooey et al., 1996; Mazzae & Garrott, 1995), so it is possible that such a display could be used for presence detection.

For imminent warnings, an auditory (or tactile) display is recommended. The main advantage of using an auditory display is that this mode is omnipresent (Sorkin, 1987) in that it does not matter where the driver is looking when the alert is issued. The driver will receive the alert in all cases, whether the driver is looking forward, scanning the mirrors, looking at the speedometer, checking the blindspot, etc. Auditory displays might be earcons (auditory icons or directionally-placed warnings) to indicate the position of a vehicle approaching from the rear adjacent lane (Kantowitz, Hanowski, & Garness, 1999; Cellario, 2001). Virtual rumble strips could be used as a warning earcon to indicate that the vehicle is near the lane border (Ledford, 2003). The work by Tan and Lerner (1996) regarding the use of voice and tone warnings should be considered. Their investigation of both voice warnings and warning tones revealed great potential for using these as in-vehicle side-object warnings.

The same rationale for using an auditory warning for an imminent warning also applies to the use of tactile warnings (i.e., they are omnipresent). In summary, it is the opinion of the author that: 1) a visual display should be used as a presence indicator (i.e., information is presented visually to depict the presence of an approaching vehicle in the left adjacent, rear lane) and 2) an auditory or tactile warning should be used to indicate an imminent warning (i.e., that a collision is about to occur) since it is unknown as to where the driver might be looking at a particular point in time. *Lane change CAS displays and alerts would need to be tested before final recommendations for implementation could be issued.*

Display Location

Making a recommendation for the best display location also involves a variety of issues that must take into consideration the complexities involved in alerting and warning drivers. Results indicate that the best location for a lane change crash avoidance system (LCAS) visual display would take advantage of natural glance patterns, as supported by Tijerina et al. (1997).

Side Locations. Mirror and side locations appear to be worthy candidates for placing warning displays. The results of the present investigation suggest that a feasible option for LCAS placement of visual displays would be integrated within the rearview or side mirror. Based on results from an experiment with a ride-along observer, Tijerina et al. (1997) made a similar recommendation. The recommendations made here substantiate Tijerina's suggestion. However, it is believed that the observations from the current experiment represent driving behavior that was unencumbered by having an experimenter present to provide directions indicating when to perform lane changes or to observe the driver. The results presented from the current experiment verify that drivers do indeed perform eye glances to the mirrors and blind spot in preparation for a lane change. For example, for left lane changes, drivers very often look toward the left (i.e., in 72% of the cases, driver glance at the left mirror, left window, or left blind spot) prior to making a lane change. Thus, placing a visual display within the mirrors or to the side may be a reasonable option, given that drivers typically look in these locations as part of their normal glance patterns.

One consideration with this recommendation is that the side locations, while accessed frequently for lane changes, are dependent upon the direction of the lane change. For that reason, it is possible that a warning presented in the side mirror might be missed if the driver is not looking at that location prior to the lane change. On the other hand, the rearview mirror is often viewed in preparation for making a lane change. In fact, for left lane changes, drivers looked at the rearview mirror at least one time in 46% of the cases; for right lane changes, drivers looked at the rearview mirror at least one time prior to performing a lane change in 43% of the cases. Since drivers often glance to the rearview mirror before making a lane change, an LCAS in this location would fit well with natural glance patterns.

However, having an LCAS display solely in the rearview mirror may not be recommended since drivers sample a variety of locations prior to making a lane change. For these reasons, it is recommended that visual displays be considered in each of the side mirrors as well as the rearview mirror. A combination system where displays are present in each of the side mirrors as well as the rearview mirror should also be considered. It is feasible that the rearview mirror could contain icons associated with both the left side and the right side of the vehicle, mapped to corresponding portions of the mirror (i.e., with a potential hazard to the left mapped to the bottom left corner of the rearview mirror). Thus, the left side mirror and the rearview mirror could contain redundant visual displays, to maximize the likelihood that the alert would be viewed by the driver during his or her mirror scanning, in preparation for performing a lane change.

Forward Location. Another potential location for an LCAS display might be in the forward view. This is because drivers spend much of their time looking forward, and this is the only location in which a driver is essentially guaranteed to look at least once while preparing to make a lane change. A feasible forward LCAS display includes the head-up display (HUD), which would take advantage of the tendency of drivers to monitor the forward view. A relatively inexpensive but effective way to implement such displays may be via the use of light-emitting diodes mounted on the dash, as mentioned in Chapter 1. The light would reflect upwards onto the

windshield, similar to what was recently done by Recarte and Nunes (2003) in their experiment investigating mental workload while driving. The HUD has been previously suggested (Mourant et al., 1969; Tijerina et al. 1997) as a format to consider, and recent advances in technology may have reduced the cost of implementing such devices. Honda has developed an experimental HUD blind-spot warning system that presents information such as vehicle location, distance, relative velocity, as well as auditory warnings if necessary (Yoshioka, Nakaue & Uemura, 1999; Yoshioka, Uemura & Nakano 1998).

Head-up displays offer advantages in that such a display could have multiple purposes, to which other warning and information systems might be linked. In fact, General Motors has recently announced that the 2004 Cadillac XLR will include an optional HUD, “to maximize the ability of drivers to keep their eyes on the road and their hands on the wheel” (DuPont, 2003). The Cadillac HUD will display information including speedometer, turn signal indicators, audio system data, gear indication, and adaptive cruise control (ACC) settings.

Considerations

As suggested earlier, a multitude of issues are involved with making LCAS design recommendations, particularly with display location. Placing displays that take advantage of natural glance patterns would likely support the driver in performing a visual check prior to making a lane change. However, a forward-based visual display, whether it is presented on or beyond the windshield, would need to be evaluated. It is possible that *as a presence detector*, forward information could be presented to depict an approaching vehicle (i.e., in the left adjacent, rear lane). However, since it is unknown as to where the driver might be looking at a particular point in time, it is not appropriate to present an *imminent warning* (i.e., that a collision is about to occur) in the forward view via a visual display.

An issue of concern is that placing additional visual information in the forward view might change behavior or elicit the wrong behavior of the driver. For example, if a driver is already looking forward, an alert presented in this location might inhibit the driver from checking his or her mirrors or the blind spot in preparation for a lane change. Another example might be the case in which the driver is looking at a location other than the forward view. A visual display presented in the forward view might not be seen if the driver is focused on another location. A warning or presence detection system should be designed so that drivers are drawn to check the location of concern (e.g., the mirrors or blind spot) when a potential hazard is detected. Regardless, the LCAS should be designed in a manner that takes advantage of the natural eye glance tendencies while driving (Lee, Olsen, & Wierwille, 2003; Tijerina et al., 1997).

As a reminder, this dissertation focuses on analyzing and understanding the behaviors of drivers as they prepare to make lane changes. No evaluation was specifically conducted to determine the best location of a LCAS. Testing of potential displays would be required before final recommendations could be made. The side mirrors and rearview mirror locations would need to be evaluated in terms of performance, preference, and likelihood of *not* contributing to distraction of the driver. That is, a system of visual and auditory displays would need to be designed that fits in well with the natural glance patterns (i.e., of checking mirrors and the blind spot) that drivers typically display during lane change latency. Although mirror locations seem to be strong candidates for LCAS displays, drivers may actually prefer the instrument cluster. Campbell, Hooley et al. (1996) reported that there was a strong preference for side object detection system displays located either in or on the dashboard, or the side mirrors; the rearview mirror was preferred less often. However, the results from the current study do not support the

suggestion that the dashboard be used for visual displays since this would draw attention downward and away from glances toward the situation outside of the vehicle.

The question as to where to locate LCAS warnings is still open to debate. On the one hand is the finding that, in essentially all cases, drivers access the forward view at least once during the three-second period prior to performing a lane change. For this reason, visual display placed forward might be warranted as an indication that a vehicle has been detected in the adjacent lane behind the driver. However, potential problems with a forward display are that: 1) it might encourage drivers to change their normal scanning patterns; and 2) if drivers are performing a variety of glances as part of their normal scan pattern, it is feasible that they might miss a forward placed display. On the other hand, a visual display placed on the side might also be missed, especially by drivers who do not regularly check the side locations. This might be due in part to a tendency to use the rearview mirror or because drivers rely on their memory of what is to the rear of the vehicle when performing lane changes. Auditory warnings, especially for imminent crash situations, would seem to hold great promise due to their omnipresent nature--since drivers can maintain their scan patterns, and a meaningful, well-designed auditory warning would alert the driver to take action to avoid a collision.

Other design considerations worthy of further investigation include the interaction of auditory warnings with turn signal use. Mazzae and Garrott (1995) recommend that auditory warnings should only be provided when the turn signal is activated (for side collision avoidance systems). Ledford (2003) states that a virtual rumble strip warning should be inactive with turn signal activation. In addition, regardless of the format of the warning, displays should be adjustable (volume and brightness) (Mazzae and Garrott, 1995).

Finally, the format (i.e., visual or auditory) of the display would still need to be determined. Results would be based upon the level of warning to be presented (i.e., as a display of the presence of a vehicle or as a warning of an imminent collision). To reiterate, the use of visual displays should be used to inform the driver that a vehicle has been detected, and an auditory warning should be used to indicate that an imminent collision is about to occur and that immediate action is required. As already stated, *the exact format and location warrants a separate research and development effort, and that is beyond the scope of this dissertation.*

Predictive Models

With the intention of identifying models that could serve as the basis for LCAS alert algorithms, six candidate predictive logistic regression models were identified to discriminate between lane changes and straight-ahead driving. Models were based upon data in which a slow vehicle was ahead and a vehicle was approaching in the rear adjacent lane. Each model was evaluated in terms of the model's ability to match the existing data. Of the six candidates, the vehicle + signal model is the most useful; this is due to its high AFCCF, sensitivity, and specificity values, and because it includes a wide variety of easily collectable data. Six regressors, including distance and TTC to the vehicle ahead, distance and TTC to the vehicle in the rear adjacent lane, brake pedal use, and turn signal timing, were entered into the model. The next most useful model was the vehicle model, since it does not rely on turn signal data. Nevertheless, it is likely that, even for cases in which the driver does not use the turn signal, the vehicle + signal model will be superior because more regressors are included. The power of these models can be increased in numerous ways. First of all, the sample of lane changes used for creating these models included some cases in which data were missing. For example, for some of the baseline events, no vehicle was ahead at the point that data was sampled. For these cases,

reasonable values were substituted for those that were missing so that the statistical package would not ignore those cases. In reality, the power of using a predictive model that includes numerous regressors lies in its ability to handle such cases. If some but not all data are missing reasonable predictions can still be made. What is more, implementation of such models for use while driving would require that data be analyzed continuously in a dynamic fashion.

Data Limitations and Work-Arounds

For the current research effort, data were taken at t_0 , a single point in time. In some cases this caused data to be missed, such as when a vehicle went out of radar range (i.e., was closer than 40 feet). To account for this limitation, rules for handling missing data were suggested to allow substitute values for TTC and distance to be entered. In some cases, estimates were also made based on review of the video data. For example, the radar typically had a minimum range of 30 feet. However, there were some cases in which a vehicle was present to the side of the subject vehicle. In these cases, distance estimates were made and entered into the data files for analysis. In addition, for the case of turn signal data, timing values were acquired by reviewing each case to determine when the signal was activated. Finally, although not a regressor in the vehicle + signal model, mirror data was based on the likelihood of glances to a particular location (i.e., probability of a glance) during lane change latency or throughout the straight-ahead event. In this way, dynamic data were implemented into an otherwise static logistic regression model.

To implement such a model in an actual system, the CAS would need to continually calculate the likelihood of a lane change. Threshold values (triggers) would be set, much as has been done for airbag deployment. Only when appropriate triggers are activated would a LCAS alert be activated, perhaps at various levels such as no alert, early, intermediate, and imminent (Brunson, Kyle, Phamdo, & Preziotti, 2002).

The possibility exists to take the recommended models here and run them at various times in a series. For example, by examining various points in time (e.g., t_3 , t_2 , t_1), it is likely that more robust models could be developed. Knowing the TTC at t_0 may be useful for understanding that a lane change is dangerous. In contrast, at that point it may be too late for the driver to respond. If, however, various TTC values prior to t_0 are also indicative of a potentially dangerous situation, it is recommended that those values be monitored continuously and used for determining when to issue an alert. Although the data is not available from this data analysis effort, the possibility of evaluating these same warning triggering criteria in future data collection efforts holds great promise--given that the same method as was used for evaluating data collected at t_0 is applied. In an actual system, TTC would be very important for issuing alerts. In fact, Talmadge et al. (1997) recommended that a warning time of three seconds TTC be incorporated into CAS algorithms, as supported by the current research (i.e., the 5th percentile for forward TTC). Note that rearward TTC was not very sensitive between lane changes and baseline. This is because there are many cases in which no vehicle was present for the lane changes, and substitute values (e.g., 30 s) filled in for those that were missing, in hopes of improving the predictive models. For distance to the rear, negative values were indicative of a vehicle that was present in the adjacent lane, but slightly forward of the rear bumper, beside the SV (Note: these data were estimated from watching video clips of the incidents, since no side radar data were available).

Improving the Models

Turn Signals. Turn signal data are important for discriminating lane change events from straight-ahead driving. A predictive model that includes turn signal data will be more powerful and would improve the reliability of the system and minimize the occurrence of false alarms. However, turn signal data are not always available, as previously discussed, with usage between 41% and 64%. For this reason, flexible models must be created that operate by making use of data other than turn signal data.

Acceleration Data. The role of acceleration rates while driving should be considered to improve model performance. Brackstone, Sultan, and McDonald (2000) reported that various speed, distance, relative velocity, and TTC at the point that the rear vehicle first begins to decelerate were important factors to include for warning algorithms relevant to collision warnings. However, the TTC (and distance) parameters assume constant speed and do not account for vehicle acceleration (Smith, Najm & Glassco, 2002). It is likely that acceleration (and deceleration) rates would be different for straight-ahead driving, as compared to the period leading up to a lane change in which a slow vehicle is ahead. It may be the case that when a vehicle is detected in the PZ, the SV often slows to let that vehicle pass before making the lane change. In other words, the acceleration rate in this case would be different compared to free-flow (straight-ahead) driving. It is logical to assume that acceleration rates may be low and perhaps less variable for free-flow driving, as compared to the period leading up to a lane change in which a slow vehicle is ahead. No acceleration data are currently available for pre-lane change periods. If data on typical acceleration rates could be collected prior to t_0 , a predictive model could use these data to improve model performance for discriminating between straight ahead and lane changing behavior for warning systems. Rakha, Snare, and Dion (2003) reported how to estimate maximum acceleration levels for various vehicles, including the same sedan that was used for this lane change project (1998 Ford Taurus) and a similar SUV (1995 Chevy Blazer). Snare (2002) offers methods for estimating typical acceleration for passenger vehicles. He suggested that 60% of the maximum acceleration rate be used to estimate typical acceleration rates. Consistent with this recommendation, the acceleration rates were computed based upon the mean velocity observed from the current study. For the sedan with a mean velocity of 61.0 mph (97.6 kmh), the acceleration would be 1.54 ft/s^2 (0.47 m/s^2); for the SUV with a mean velocity of 58.6 mph (93.7 kmh) the acceleration would be 1.34 ft/s^2 (0.41 m/s^2).

Although no acceleration data are currently available, it is possible that car-following acceleration/deceleration rates could be used as part of lane change prediction models. That is, if data on typical acceleration rates could be collected, then a prediction model could use these rates to help distinguish between straight-ahead driving and lane change events. It is likely that, when changing lanes, the following vehicle slows (decelerates) behind the slow lead vehicle before preparing to change lanes. Often, other vehicles are present in the adjacent lane and the gap is not clear, so the driver decelerates to maintain a safe gap ahead until the lane change can be made. Therefore, acceleration rate should be considered (i.e., monitored continuously) to improve the performance of a predictive model in discriminating between straight ahead and lane changing behavior for warning systems. In fact, Brackstone et al. (2000) suggest that monitoring the brake and accelerator pedals would be beneficial to understanding driver behavior when a slow lead vehicle is encountered, and this may perhaps be a contributing factor in issuing collision warnings.

Lane Position. It is recommended that lane position data be made available as well. A camera, radar, or laser-based lane tracker could both predict lane changes, as well as assist drivers in maintaining lane position and to avoid run-off-the-road incidents. During a lane change, the duration from lane change initiation to the point at which the vehicle begins to cross the lane line is approximately 1.3 to 2 s in length, based on informal observations of numerous lane change events and according to Worrall and Bullen (1970). Thus, tracking lane position will help with predicting lane change likelihood so that alerts can be issued in a timely manner as needed. In fact, an early version of such a lane tracker, known as Road Scout, has been deployed for use in a large on-road field experiment (Neale, Klauer, Dingus, Holbrook, & Peterson, 2001). The lane tracker “determines location and characteristics of a roadway in real time onboard a moving vehicle using a camera that looks through the front windshield of a car,” and was invented by software and hardware engineers at the Virginia Tech Transportation Institute (VTIP, 2001).

Side Object Detection. Additionally, side sensors would likely enhance the ability of a LCAS to monitor the safety zone around the vehicle. Having side sensors would provide lateral data relevant to lane position. Mazzae and Garrott (1995) evaluated side object detection systems (SODS) for use by commercial truck drivers. Although data did not suggest that driver performance was improved using SODS, it is likely that information employing similar technology could be used by a multiple-regressor predictive model to assist drivers in assessing their surroundings before making lane changes. Other research efforts have supported the use of side object detection data. In fact, in 1995, NHTSA launched the Automotive Collision Avoidance Systems (ACAS) program to support development “implementation of a comprehensive collision warning system, which is capable of detecting and warning the driver of potential hazard conditions in the forward, side, and rear regions of the vehicle” (NHTSA, 2000c, Executive Summary). Such a system would include sensors to detect side objects and lane information to warn drivers when a hazard is present. For example, TRW recently developed a system that uses a scanning laser rangefinder to monitor areas surrounding the vehicle, including vehicle directly next to the test vehicle (Talmadge, Chu, & Riney, 2000). Future systems could make use of side-mounted cameras to detect objects as well (B. Leeson, personal communication, October 2, 2003). Regardless of how such data are collected, having this information would greatly improve the ability of predictive models.

Eye and Head Movements. The analysis revealed that eye glance data is an important predictor of lane change initiation and should, ideally, be integrated into predictive models. Although glance data would be useful for expanding LCAS functionality, a model including glance data would not be practically feasible at the current time. To be useful, the predictive model would need to include glance data that is processed *while driving*. Currently, these data are only available after extensive data preparation. However, to allow such a model to be used by a LCAS model, an unobtrusive (and accurate) eye/head tracker would be required. For example, Recarte and Nunes (2000; 2003) used such a system to track eye position with an infrared video camera installed on the dashboard to monitor pupillary dilation and visual search while driving. It is likely that future vehicles could include unobtrusive eye or head monitoring devices so that such data could be incorporated into predictive models. Analysis has revealed that glances to the rearview mirror, left mirror, and left window are important to monitor, particularly for left lane

changes and would greatly improve the ability of models to discriminate between lane changes and straight-ahead driving.

Integration with Other Systems

To maximize effectiveness, lane change crash avoidance systems (LCAS) should be integrated with other CAS and other vehicle systems. Various systems are currently being introduced into vehicles. Lane change CAS should be complementary to these systems so that warnings or alerts are meaningful and not confused with those from other systems.

Lane Keeping/Run-off-the-Road Systems. Systems are being developed to assist drivers in maintaining lane position to avoid run-off-the-road incidents or to alert drivers when they are near the lane border (Antonello, Vivo, & Burzio, 1995; Bertozzi & Broggi, 1998; Ledford, 2003). Such systems act as road lane monitoring systems by using sensors such as cameras to detect lane lines. Alerts are then issued as needed, by such means as an auditory tone (Antonello, Vivo, & Burzio, 1995) or an earcon such as a virtual rumble strip (Ledford, 2003), when the car is near the lane border. Future systems might include variable resistance steering (Chovan et al., 1994) or automated vehicle control for maintaining lane position.

Enhanced Turn Signal System. It is feasible that an enhanced turn signal-activated system could be created that would only engage when conditions are safe. These systems might be expansions of the currently used turn signal activators to maximize acceptance and understanding by drivers. Such a system might actually be a form of display to be used with lane keeping, run-off-the-road, or lane change assist systems. Warnings would be issued as needed using visual displays that are enhancements of current turn signal displays with various arrows and colors, with additional displays such as tactile or auditory displays.

Automatic (intelligent) cruise control (ACC) or forward CAS. For LCAS to be successful, it is important that ACC and forward CAS warnings be integrated so that information is presented to the driver that is easy to understand and respond to. Maintaining a safe distance and TTC from vehicles ahead at all times is highly desirable, and numerous systems are under development. For example, in 1998, Mercedes-Benz introduced an adaptive cruise control system called Distronic that uses a radar sensor and a computer to constantly maintain a safe distance from the vehicle ahead (DaimlerChrysler, 2001). Infinity now offers an intelligent cruise control system on the Q45, M45, and FX45 models. The system is laser-guided to automatically maintain a fixed distance (from 105 to 195 feet) from a vehicle ahead, after setting the desired speed. The system controls acceleration and will not apply any more than 25 percent of available braking power (Houston, 2003; Nissan, 2003). Other manufacturers are offering ACC as well, including General Motors (Cadillac XLR), Jaguar, Lexus, and Nissan (Barneden, 2003; DuPont, 2003).

Eye Position/Fatigue Monitoring. The ability to unobtrusively monitor eye (and head) movements in terms of direction, duration, and closure is on the horizon. As previously discussed, Recarte and Nunes (2000; 2003) used an infrared camera-based system to track eye position while driving. A related approach is that of Wierwille et al. (2003), which monitored drivers using a remote, unobtrusive system that automatically monitored eyelid droop. This was a PERCLOS monitoring system known as The CoPilot[®]. The system uses cameras aimed at the

eye and that processes eyelid information online during operation. The next step would be to implement refined versions of such systems so that output could be analyzed while driving. The results would be used by the public at large for predicting lane change intention and the likelihood of an unintentional lane crossing due to driver fatigue. Such systems could greatly enhance driver safety.

Driver Assessment. As previously mentioned, it is likely that future systems will continually monitor driver and vehicle parameters and provide driving assessment based upon actual driver data. Relevant and interesting feedback could be summarized and offered to the driver periodically in a customized format. This data might include velocity, following distance, fuel consumption, lane change rate, turn signal usage, and “close-call” data, with an aim of improving driver performance and awareness. Feedback could be offered to the driver in various forms such as auditory messages that are delivered in easy-to-understand language when surrounding conditions are relatively safe. The basis of such a system (without video data) appears to be represented by the RS-1000 black box (Road Safety, 2002).

Workload Management. A workload management system would monitor the driver and manage driver input in an attempt to control workload. If a particular stimulus limit is met, the system would curtail additional input until workload levels decrease. For example, if a driver is in dense traffic, is about to make a lane change, and a phone call is received, the system will suppress the phone call until the driver is in a safe, less stressful situation. Such a system could be integrated with a driver assessment system as well. Chrysler recently introduced such a system, called the “Driver Advocate” into the Town and Country minivan (Buchholtz, 2003). The purpose of the system is to evaluate incoming messages and suppress non-urgent messages during potentially distracting periods. Existing sensors will be used with additional sensors and controls placed in conjunction with the steering wheel.

Vehicle-to-Vehicle/Device Communication. In the future, vehicles will share information with other vehicles/devices about their vehicle, traffic, road condition, traffic control devices, as previously mentioned. Dedicated Short Range Communications (DSRC) radio transmission technology (Kelly & Johnson, 2002) will deliver messages to and between vehicles and infrastructure to allow the sharing of data so that potential hazards could be avoided (Huang et al., 2001).

Lane Change Auto-Pilot. Future systems might included an advanced LCAS that would operate analogous to an ACC system; when the system is active, safe lane changes would be performed smoothly and automatically using braking, acceleration, steering, and communication to surrounding vehicles using turn signals and via other means. Such a system would follow the concept of “auto pilot” for airplane landing descents, in that performing lane change would be assisted or controlled automatically.

Limitations

Environment

Various limitations were present in this study. First, all data were collected in a rural environment in southwest Virginia. While traffic does fluctuate in terms of density and vehicle type (e.g., number of trucks), the overall tempo of driving and lane changes is likely to be more

conservative, as compared to urban environments such as Washington, D.C., Los Angeles, California, or other heavily populated areas in which multiple-lane roadways and very dense traffic is an everyday occurrence. The actual process of performing lane changing is not likely to vary among various parts of the country; however, the gaps between vehicles, velocities, and turn signal use would undoubtedly differ as a function of factors such as lane count and width, traffic density, time of day, weather, and road conditions.

Data Format

As previously discussed, the data collected for this dissertation was largely static in nature in that data were sampled at a single point in time, namely t_0 . Descriptive and statistical analysis, logistic regression model development, and the conclusions were based upon these data. In response to this limitation, data such as eye glance probability and turn signal timing was reviewed at numerous points in time and used as a substitute for truly dynamic data. In some cases, data were missing and substitute values were used. Relevant data such as distance, TTC, acceleration and deceleration, eye glance position, turn signal use, lane position, and side object detection would, ideally, be available for use with actual LCAS. This would require the addition of side sensors, a lane tracker, and unobtrusive eye monitoring equipment. Predictive warning models should be able to continuously analyze data; these models would be based on live calculations of lane change likelihood, using alert thresholds for proper warning.

Collection and Analyses

A final limitation was the time and resources required to collect and analyze on-road field data aimed at capturing actual driving performance. The time and effort required to instrument vehicles, recruit participants, collect data, identify and analyze data, create operational definitions, train analysts, develop software, perform eye glance analysis (i.e., frame-by-frame), digitize video clips, and make data usable for statistical analysis was immense. Prior to data collection, a candidate data collection system was analyzed for approximately four months and was deemed unsuitable for eye glance analysis. A modified in-house data collection system was then proposed for use and accepted. In addition, two separate reviews were required for this experiment since both the Virginia Tech Institutional Review Board (IRB) and a NHTSA Human Use Review Panel (HURP) and were involved. The IRB process was relatively quick; however, the HURP was delayed for several months due to the Firestone recall that took place on August 9, 2000, with which NHTSA administrators were heavily involved. Data collection finally began in October, 2000 and ended in July 2001. Kirakowski (1997) reported that analysis of data usually takes five to seven times the amount of time spent recording events, requiring access to specialized recording and playback equipment. This was surely the case for this effort. Prior to data analysis, operational definitions for event identification were formed, and selection and training of data analysts was also conducted. Event identification alone took approximately six months, with approximately 10% of events spot-checked for consistency among raters. Ideally, more time would have been spent to check inter-rater reliability. However, it is believed that the training implanted was sufficient to maximize reliability among analysts. Data analysis took five additional months to complete. A final draft for the original NHTSA effort was completed in November 2002, and the final draft was accepted on January 24, 2003. Throughout this larger NHTSA effort, the proposal for this dissertation effort took place, with the initial proposal being accepted May 30, 2002. Since the inception of the original experiment in 1998, almost five years have elapsed. Although useful information has been acquired, the “shelf life” of the data may be

limited because in-vehicle and other technology is changing at a rapid pace. Regardless, it is believed that this archive of data is one of the largest sets of “normative” driving data collected from an on-road field experiment under realistic, everyday driving conditions.

Future Research

Several areas exist that are ripe for further investigation. One such topic area is the effect of introducing new technology on driver behavior. The recommendations that LCAS displays be placed in the forward view or to the sides are based on normal driving conditions with no special equipment. Further research is needed to determine how the addition of such systems may influence driver behavior. The levels of warning and formats would need to be evaluated in realistic settings, with a variety of driver types before implementation is considered.

Another topic area is the issue of turn signal use. The reasons that drivers do not use turn signals before a lane change are unknown. It may be possible that drivers believe there is no need to signal if they think that no other vehicles are nearby. Other drivers may believe that signaling encourages others to close and block the gap if they were to let the driver behind them know they are going to change lanes. Some drivers may assume that the surrounding drivers know their intentions, especially if a vehicle had been in the vicinity for a long period of time or had just been passed. Drivers may believe an upcoming lane change “is obvious,” such as for the case when a large, slow semi-truck is ahead; the driver performing the lane change may assume that drivers in the rear area can also see the truck and would anticipate that the vehicle behind would change lanes. Other reasons for not using turn signals may be related to lack of planning or lack of proper driver training. Drivers may not have “developed the habit” of using turn signals prior to performing maneuvers. In rare cases, it is possible that turn signal activators are not operating correctly. Investigation into the reasons for not using turn signals may be a worthy endeavor. The turn signal is a form of communication to other drivers, indicating intention of movement, and increased use of signals would improve the safety of all drivers.

A large question remains about the awareness of drivers in relation to the presence of surrounding vehicles. Previous driving research indicates that drivers are not aware or do not otherwise recognize that a hazard is present before making a lane change or many other kinds of maneuvers (Chovan et al., 1994; Eberhard et al., 1994; Knipling 1993; Tijerina, 1999). The “looked but did not see” phenomena may be part of the problem and should be researched further. Until in-vehicle warning technology is developed, evaluated, accepted, and implemented into vehicles of the future, driver training and education for new and experienced drivers should be enhanced (Hendricks, Fell, & Freedman, 1999). Such training should focus on teaching proper scanning techniques and could include data communicating the magnitude of the problem, case studies, and perhaps video clips from actual on-road situations demonstrating both poor and proper behaviors.

Further research may include additional secondary data analysis of the data archives. Analysis of acceleration or deceleration rates prior to lane changing would be useful for knowing when and if a lane change is going to occur (Brackstone, Sultan, & McDonald, 2000). In fact, acceleration or deceleration rates are likely to change even before the first lateral movement of a lane change. Analysis of the lead vehicle type might also be considered in terms of the vehicle type and its effect on TTC, distance, and likelihood of a lane change. For example, drivers may change lanes with a different frequency or with a different style when the slow lead vehicle is a passenger vehicle or light truck or large truck. Finally, the effect of in-vehicle tasks such as

interaction with radio or climate controls, personal items, and cellular phones on driving should be investigated for their influence on lane changing.

As a final note, research is needed to address the effect of having multiple CAS in vehicles (NHTSA, 1997); in fact, such research has recently been launched in a combined effort by NHTSA, Dynamic Research, Inc., and Westat, Inc. (Foley, 2003).

Summary

Awareness of driving hazards has been an issue of concern since Henry H. Bliss was struck and killed by an automobile in 1899. The societal cost of transportation-related incidents has been a continual problem ever since. Driver education, training, and awareness programs have been designed to enhance driving safety and awareness of road hazards. However, the continual expansion of roadways and vehicle-information systems have put higher demands on today's drivers. Remaining aware while driving is problematic due to the barrage of input available that requires a level concentration that is difficult to continually maintain. In-vehicle technology is being incorporated into vehicles at an increasing rate. Such technology may be part of the problem because additional information will be made available to the driver. Nonetheless, this same technology can help the driver to increase and maintain awareness so that safety can be maximized and injuries and fatalities minimized. Increased investment toward the development of crash avoidance systems (CAS) has occurred in response to pressure to reduce roadway congestion and to reduce both crash incidence and crash severity, a likely result from implementing such technology (Brackstone, Sultan, & McDonald, 2000; Knippling, 1993). The goal of an LCAS is to extend the ability of the driver by monitoring surrounding areas when preparing to make a lane change. The net result would not only reduce incidence and severity of lane change crashes but would contribute to a reduction in society costs, time-delay, and property damage as a result of lane change crashes.

Many previous data collection efforts have had limitations because of obtrusive equipment and experimenter presence. This has led to the need for on-road experimentation, during which drivers are likely to exhibit behaviors that are representative of everyday driving. The type of lane change analyzed was the slow lead vehicle lane change, in which a vehicle was ahead in the same lane that was to be passed. This is a common maneuver, accounting for over one-third of all lane changes. These maneuvers were available from a previous data collection effort (Lee, Olsen, & Wierwille, 2003) from which a sample was selected and analyzed in-depth.

What was discovered has important relevance for characterizing lane changes and for understanding LCAS design in terms of warning levels, display mode, location of displays, required data, and integration with other systems.

Analysis revealed that interstate lane changes were performed least often with lower urgency ratings, as compared to highway lane changes. Interstates are designed for smoother traffic flow due to a lower likelihood of vehicles such as farm tractors. In addition, on and off ramps are designed to assist drivers in accelerating or decelerating to maintain traffic flow. In addition, data analysis of normative lane change frequency indicated that drivers who usually drive sedans were more likely to make lane changes than drivers of SUVs, suggesting that drivers maintained their driving style regardless of which experimental vehicle was driven.

Behaviors were analyzed during lane change latency, prior to lane change initiation. Analysis of turn signal use indicated that, at most, just over half of drivers do use turn signals when making lane changes. Of cases in which signals were not used, 70% of them were made with other vehicles nearby.

Analysis of eye glance behavior revealed that distinctive eye glance differences were discovered in association with straight-ahead driving and lane changing, with large proportions of glances to the forward view in both cases. A relatively large proportion of glances prior to lane change initiation occur to the windows, mirrors, and blind spots associated with the direction of the lane change to be completed. During straight-ahead driving, glances are distributed among various locations, including instrument cluster, rearview mirrors, and other locations including on both sides of the vehicle. However, unlike for lane changing, blind spot checks are almost non-existent.

Logistic regression analysis revealed that the single best model would be the vehicle + signal model that takes advantage of distance to the front and rear adjacent vehicle, TTC to the forward vehicle, and turn signal activation information. Additional regressors would improve the model that includes brake activation and TTC to the rear adjacent vehicle. Also, if data were available related to acceleration or deceleration, eye glance position, lane position, and side-object detection, predictive power would be increased.

This dissertation focused on avoiding lane changing crashes resulting in a relatively low percentage of fatalities. However, lane change crashes resulted in a moderate percentage of all police reported crashes that included substantial injury, property damage, additional societal costs, and almost 10% of all crash-caused delay. In fact, the same sensors and algorithms used for avoiding lane change crashes may also be used to reduce the even larger number of vehicle fatalities in which lane keeping and run-off-the-road were a factor, accounting for 44% of all vehicle fatalities. Systems of the future must be designed in an integrated manner so that sensors and displays guide the driver to greater awareness of potential hazards. Lane change CAS should be integrated with other vehicle systems to maximize effectiveness, safety, and acceptability. The implementation of systems such as ACC, HUDs, workload management and assessment, and automated vehicle communications would need to be considered before successful implementation of LCAS. Future research of integrated systems is required; in fact, an effort was launched in June 2003 by Dynamic Research Inc., in conjunction with Westat, Inc. and NHTSA to evaluate the impacts of multiple crash alarms on driver performance, including analysis of alarms from independent and non-integrated CAS (Perel, Llaneras, Weir, & Chiang, 2003). As a reminder, the design guidelines created for this dissertation were created as a stand-alone document and are intended to aid designers in developing advanced warning systems.

Additional research might be conducted on a variety of relevant topics, including turn signal use, driver awareness, in-vehicle tasks, effect of lead vehicle type, and acceleration and deceleration rates prior to lane change initiation. In fact, it is possible that some of these issues could be addressed by further secondary analysis of the data established in association with the current effort and other data archives, without the need to collect further data. Finally, it is recommended that public awareness campaigns, training, and education be supported to disseminate the findings from this effort and to raise awareness about the need for concentration and awareness of the present moment while driving for drivers of all abilities, types, and experiences. A video entitled "Avoiding Collisions While Passing & Being Passed" (#990322, 1990) is available from the Virginia Department of Education, Office of Production Services, S-Level, 101 N. 14th Street, Richmond, Va. 23219 that can be borrowed by visiting <http://www.pen.k12.va.us/VDOE/Instruction/PE/drivereddoc.pdf> or by calling (804) 692-0336. The video, in a simplistic cartoon format, is intended for new drivers.

In all, there are two factors that lead to successful and safe lane changing: 1) using turn signals every time a lane change is made as a form of communication to other road users, and 2)

making a head turn to check blind spots (AAA, 2003; Chovan et al., 1994). If such information could be disseminated to the public at large, lane change incidents and severity would be lessened. In conjunction with such an effort, technology in vehicles will assist drivers to remain aware of the situation at hand, allowing drivers to develop and maintain safe driving habits.

CHAPTER 6: DESIGN GUIDELINES

Design guidelines were developed based on analyses of the available data. The purpose of each guideline is to present recommendations for designers of lane change collision avoidance systems. Five guidelines have been provided: warning levels, display modality, display location, data relevancy, and system integration.

Each design guideline is based upon an investigation comparing a set of 120 lane changes in which a slow lead vehicle was present to a set of straight-ahead (baseline) driving events and in which no lane change occurred. Data were collected for drivers who drove an instrumented vehicle to and from work over a period of 20 days, with no experimenter present. Each maneuver was analyzed in terms of aspects such as duration; turn signal use; eye glance patterns, with particular emphasis on the three seconds prior to lane change initiation, since critical driver decisions must be made during that time period. For straight events, the entire event was analyzed. In addition, relevant references were used extensively.

These recommendations were developed based upon drivers' natural inclinations in terms of eye glance patterns and turn signal use, as well as on the assumption that an LCAS should not disrupt these natural patterns. Other approaches to the design problem might involve changing the driver's behavior in some way, but these approaches are not considered here. Nonetheless, designers using other design approaches should still find the guidelines presented to be useful. In some cases, guidelines include findings from other related research efforts.

A standardized and easily understood format has been created. This new format is based upon that used by Campbell, Carney, and Kantowitz (1998), including relevant quantitative data for use by designers (where possible). Each guideline includes the following elements: 1) an introduction defining the design guideline; 2) quantitative design guideline, table, or figure; 3) supporting rationale, based on relevant literature and findings from the current research effort; and 4) references. This chapter is intended to be a stand-alone document, separate from the larger supporting document (the associated dissertation) by Olsen (2003).

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Warning Levels

Introduction: Warning levels refer to alerts to be issued under various circumstances related to likelihood of collision. A presence detection indicator and an imminent warning are recommended.

Warning issuance is to be based upon a dynamic model considering forward and rearward distance, forward and rearward TTC, brake pedal use, turn signal activation, acceleration, lane position, and eye glance behavior. Simple alert mechanisms can exclude signal and eye glance data, but effectiveness will not be maximized. The parameter ranges are offered as a starting point--*various combinations must be tested before implementation*--this table is for left lane changes. Testing and validation would be required before implementation of these recommended warning levels. The presence detection level is an indication of a vehicle that is present within the range of the sensor(s), and the imminent warning level is associated with an imminent collision (i.e., if no action is taken).

Alert Levels and Associated Warning Parameter Ranges.

	FDist	FTTC	RDist	RTTC	Brake	sig_on	Accel	Lane Position	Eye Glance location
Unit	feet	seconds	feet	seconds	%	%	ft/s ²	in. from center	direction
Pres. Det.	≥ 75	> 3.5	≥ 30	> 3.5	Off/on	Off/on	≥ 1.5	< 30	Any location
Imm.	< 75	≤ 3.5	$-20 < x < 30$	≤ 3.5	On	On	< 1.5	≥ 30	RVM, LM, LW, LBS

Supporting Rationale: Warning levels were loosely modeled after the NHTSA rear-end collision alert algorithm, including no alert, early, intermediate, and imminent (Brunson, Kyle, Phamdo, & Preziotti, 2002). However, multiple-stage warning systems may be difficult to comprehend and understand, given that lane changes are performed very quickly. That is, the period of time from lane change initiation to the point at which the vehicle begins to cross the lane line is approximately two seconds. A modification of the NHTSA paradigm should be used for an LCAS. The presence detector indicator and only one level of warning (imminent) are practical.

An LCAS is intended to aid the driver in making decisions about whether or not to initiate a lane change. Prior to receiving a warning, a presence detection display would be used. This display would provide information to the driver about the presence of a vehicle in the rear adjacent lane (i.e., in the fast approach zone or proximity zone) any time such a vehicle is detected. The vehicle presence level indicates a vehicle is detected by the sensor(s), and it is meant to provide information to the driver even in no lane change is likely.

An imminent warning would only be issued to warn the driver when the system predicts that a lane change is about to occur and a vehicle is approaching or detected in the rear, adjacent lane or zone. This would be considered an imminent warning because, if the present situation continues and no action is taken, a collision is imminent.

The previous table is based on various sources. Forward distance values was based upon data from Olsen (2003) and Lee, Olsen, & Wierwille (2003) in which a mean of 109 feet ($SD = 75$) was observed; the 5th percentile values were considered the minimum likely values. Values reported by Brunson et al. (2002) were used to adjust values upward. Forward and rearward TTC

values were based on findings from Talmadge et al. (1997) and Olsen (2003) for setting the imminent level. Rear distance cut-offs were based upon zones behind and beside the vehicle and were derived from the work of Talmadge, Chu, & Riney (2000). This parameter could be complemented with side-sensor (lateral distance) data, if available. Imminent cut-off values for rear distance were estimated for the case in which a vehicle was anywhere in the blind spot. Without side sensor data available, this value was estimated to be in the range of 15 feet (5th percentile) in front of and 21 feet (25th percentile) behind the vehicle in the adjacent lane.

Brake, signal, and eye glance data were based upon Olsen (2003), comparing lane changing to straight-ahead driving. It is more likely for drivers to use the brake before a lane change than during straight-ahead driving. Turn signal activation is a strong predictor of lane change likelihood, although only 41% of lane changes involve activation before the lane change starts (Olsen, 2003; Lee, Olsen, & Wierwille, 2003). Eye glances to the rearview mirror, left mirror, left window, and left blind spot are two to nine times more likely to occur during the period just before a lane change, as compared to straight-ahead driving (Olsen, 2003).

Lane position was loosely based on Worrall & Bullen (1970), who broke the lane change into portions and informal analysis of lane changing data in which mean deviations from the center line were evaluated by consulting archived data. Acceleration data needs to be acquired for the pre-lane change periods; however, only estimates are available for straight-ahead driving, as is indicated in the work of Snare (2002) and Rakha, Snare, and Dion (2003). Warning algorithms using acceleration would be more powerful than those that do not (Chovan et al., 1994).

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Display Modality

Introduction: The warning display modality refers to the mode in which warnings should be presented. Both visual and auditory displays should be considered, with auditory and tactile warnings used for imminent alerts.

A visual display should be used as a presence indicator (i.e., information is presented visually to depict the presence of an approaching vehicle in the left adjacent lane, rear lane, or rearward zone).

Since it is unknown as to where the driver might be looking at a particular point in time, an auditory or tactile warning should be used to indicate an imminent warning (i.e., that a collision is about to occur). A tactile display may be considered in conjunction with or in place of the auditory warning. Before implementing these displays, experimentation and testing is recommended.

Note that a system built-in-test (BIT) indicator, while not part of the warning system used while the vehicle is in operation, would include a visual/auditory indicator that is presented when the vehicle is first started up. These indicators would be similar to those that are used for other status indicators such as for ENGINE and AIRBAG indicators, which are available in most modern vehicles. An auditory confirmation tone of proper operation should also be presented at this time.

Display Types For Various Alert Levels

Alert Level	Display Type	Display Format	Status	Notes
System BIT	Visual with auditory confirmation	Icon with auditory tone	Blinking State for 1-3 s at vehicle start-up	Green blinking indicates operational; BIT of auditory system at startup
Pres. Detect.	Visual	Visual light in right/left side mirror, or possibly in HUD	Continuous light or blinking light (possibly for 1-2 seconds when first detected)	Light off when danger gone; likely to use red or amber
Imminent	Auditory and/or tactile	Tone/voice, and/or vibration	Auditory tones/voice and/or tactile feedback until action taken	Buzz tone, voice, or earcon (e.g., rumble strip); warning issued if rear, adjacent vehicle detected and algorithm detects a lane change is likely.

Supporting Rationale: Warning displays should be visual for the no-alert and early warnings (Mazzae & Garrott, 1995; Campbell, Carney, & Kantowitz, 1998). This supports the concept of a presence indicator presented in a visual format. Steady amber or red lights should be used for cautionary warnings (Campbell, Hooey et al., 1996; Mazzae & Garrott, 1995), so it may be possible that such a display is used for the presence detection display.

A built-in-test (BIT) indicator that illuminates momentarily when the vehicle is turned on and continuously if a system failure is detected (Mazzae & Garrott, 1995) should be used. This indicator may be an additional system status light integrated into the instrument panel or within the mirror (s); however, the format (color) of the system failure status indicator should be

evaluated to assure that operators understand it, and do not mistakenly assume that the system is operating normally if a system failure is to occur. Previous recommendations have suggested that a steady green status light should be used to indicate that the system is active and working properly or to confirm there is nothing in the blind spot (Campbell, Hooey et al., 1996; Hyland, 1995). However, this is not recommended due to the potential for liability and driver distraction issues. During normal operation, it is recommended that LCAS visual displays only be illuminated when a vehicle is present (i.e., via a red indicator light). A green “go” light is not recommended.

It is assumed that the visual indicator would be a steady state. However, if blinking is considered, the blink rate should be 4 Hz (0.25 s) with equal on and off durations (Campbell, Hooey et al., 1996; Dingus et al., 1997). If visual displays include text or iconic information, the hold time should be a minimum of 0.5 s (Hyland, 1995). *Warning modality for LCAS alerts should be tested before implementation.* The number of warning levels would need to be evaluated because lane changes and lateral movement can occur quickly, and drivers might have difficulty comprehending two or three alerts if they were issued within a very short period of time. For example, it may be discovered that only the early (presence detection) and the imminent alert levels would be recommended. In order to determinate acceptance and false alarm rates, based on testing and evaluation, threshold values would likely need to be set and adjusted as well.

For imminent warnings, an auditory (or tactile) display is recommended. The main advantage of using an auditory display is that this mode is omnipresent (Sorkin, 1987)--it does not matter where the driver is looking when it is issued. The driver will receive the alert in all cases, regardless of whether the driver is looking forward, scanning the mirrors, looking at the speedometer, checking the blindspot, etc. Auditory displays might be earcons (auditory icons or directionally-placed warnings) that would indicate the position of a vehicle approaching from the rear adjacent lane (Kantowitz, Hanowski, & Garness, 1999; Cellario, 2001). Virtual rumble strips could be used as a warning earcon to indicate the vehicle is near the lane border (Ledford, 2003). The work by Tan and Lerner (1996) regarding the use of voice and tone warnings should be considered. Their investigation of both voice warnings and warning tones revealed great potential for using these as in-vehicle side-object warnings. The same rationale for using an auditory warning for an imminent warning also applies to the use of tactile warnings (i.e., they are omnipresent). *Lane change CAS displays and alerts would need to be tested before final recommendations for implementation could be issued.*

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Display Location

Introduction: Making a recommendation for the best display location also involves a variety of issues that must take into consideration the complexities involved in alerting and warning drivers. Results indicate that the best location for a lane change crash avoidance system (LCAS) visual display would use natural glance patterns as a presence indicator.

Design Guidelines			
Location	Forward Visual Display	Side Visual Display	Rear View Mirror Display
Advantage	<ul style="list-style-type: none"> ▪ All drivers look forward prior to a lane change ▪ Good location for presence detection display 	<ul style="list-style-type: none"> ▪ Most drivers (72%) look to the side (i.e., left mirror, left window, or left blind spot) prior to a left lane change ▪ Fair location for presence detection display 	<ul style="list-style-type: none"> ▪ Many drivers (43% to 46%) look in rearview mirror prior to lane change ▪ Fair location for presence detection display
Disadvantage	<ul style="list-style-type: none"> ▪ Might cause driver to maintain forward glance longer than normal ▪ Not recommended for imminent collision 	<ul style="list-style-type: none"> ▪ Might be missed if driver looking elsewhere ▪ Not recommended for imminent collision 	<ul style="list-style-type: none"> ▪ Likely to be missed if driver looking elsewhere/does not check rearview ▪ Not recommended for imminent collision

Supporting Rationale: A feasible option for LCAS placement of visual displays would be integrated within the rearview or side mirror. Tijerina et al. (1997) made a similar recommendation. Drivers regularly perform eye glances to the mirrors and blind spot in preparation for a lane change. For left lane changes, drivers very often look toward the left (i.e., in 72% of the cases, driver glance at the left mirror, left window, or left blind spot) prior to making a lane change. Thus, placing a visual display within the mirrors or to the side may be a reasonable option.

However, the side locations are dependent upon the direction of the lane change, and it is possible that a warning presented in the side mirror might be missed if the driver is not looking at that location prior to the lane change. On the other hand, the rearview mirror is often viewed (i.e., 46% of the time for left lane changes) in preparation for making a lane change. An LCAS in this location would fit well with natural glance patterns. A combination system in which displays are present in each of the side mirrors and the corresponding portion of rearview mirror should also be considered. Such a system would maximize the likelihood that the alert would be viewed by the driver during his or her mirror scanning.

Another potential location for an LCAS display might be in the forward view. This would be an ideal location because drivers spend much of their time looking forward, and this is the only location to which a driver it is essentially guaranteed to look at least once while preparing to make a lane change. A feasible forward LCAS display includes the head-up display (HUD). The HUD has been previously suggested (Mourant et al., 1969; Tijerina et al. 1997) as a format to

consider, and recent advances in technology have likely reduced the cost of implementing such devices. Eberhard, et al. (1995) suggested that the HUD display is preferred over rearview mirror displays. Existing systems should be evaluated, specifically Honda's experimental HUD blind-spot warning system (Yoshioka, Nakaue & Uemura, 1999; Yoshioka, Uemura & Nakano 1998), the GM HUD (DuPont, 2003), and the Simens HUD used by BMW (Costlow, 2003). Head-up displays offer advantages since such a display could have multiple purposes, to which other warning and information systems might be linked. For example, General Motors has recently announced an optional HUD that will display speedometer, turn signal indicators, audio system data, gear indication, and adaptive cruise control (ACC) settings (DuPont, 2003). Specifics on HUD image location and distance can be obtained by reviewing Campbell, Carney, & Kantowitz (1998). A relatively inexpensive but effective way to implement a HUD may be via the use of light-emitting diodes mounted on the dash; the light would reflect upwards onto the windshield, similar to what was recently done by Recarte and Nunes (2003).

Regardless of the location (i.e., forward or side), any potential visual display should be evaluated before implementation. It is possible that *as a presence detector*, visual displays could be used to depict an approaching vehicle (i.e., in the left adjacent, rear lane). However, since it is unknown as to where the driver might be looking at a particular point in time, it is not appropriate to present an *imminent warning* (i.e., that a collision is about to occur) via a visual display. Presenting additional visual information might change behavior or elicit the wrong behavior of the driver. A visually presented alert might be missed or otherwise not be seen if the driver is focused on another location. A warning or presence detection system should be designed so that drivers are drawn to check the location of concern (i.e., the mirrors or blind spot) when a potential hazard is detected. Regardless, the LCAS should be designed in a manner that takes advantage of the natural eye glance tendencies while driving (Lee, Olsen, & Wierwille, 2003; Tijerina et al., 1997).

The question as to where to locate LCAS warnings is still open to debate. On the one hand is the finding that, in essentially all cases, drivers access the forward view at least once during the three-second period prior to performing a lane change. For this reason, a forward placed visual display might be warranted as an indication that a vehicle has been detected in the adjacent lane behind the driver. However, potential problems with a forward display are: 1) it might encourage drivers to change their normal scanning patterns, and 2) if drivers are performing a variety of glances as part of their normal scan pattern, it is feasible that they might miss a forward placed display. This might be due in part to a tendency to use the rearview mirror or because the driver relies on his or her memory of what is to the rear of the vehicle when performing lane changes. On the other hand, a visual display placed on the side or in the rearview might also be missed, especially by drivers who do not regularly check the side locations.

The side mirrors and rearview mirror locations would need to be evaluated in terms of performance, preference, and likelihood of *not* contributing to distraction of the driver. That is, a system of visual (and auditory) displays would need to be designed that fits in well with the natural glance patterns (i.e., of checking mirrors and the blind spot) that drivers typically display during lane change latency. It is likely that visual displays should be used for presence detection, displaying information as soon as it is detected. However, due to their ubiquitous nature, auditory warnings should be used for imminent crash situations. Finally, *the exact location (and exact format) warrants a separate research and development effort*. Testing will be required before implementation to assure safety and reliability.

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Data Relevancy

Introduction: Data relevancy refers to the recommended data that should be used as the basis for developing LCAS warning algorithms.

To discriminate between lane changes and straight-ahead driving, analysis from Olsen's (2003) data revealed that the most relevant data are time-to-collision (TTC), distance (range), and brake data that are based on the logistic regression. In addition, turn signal, eye glance, side-object, and acceleration/deceleration data, if available, should also be incorporated into predictive models to improve performance. Predictive models for use in actual systems should evaluate data at all times at a rate of at least 10 Hz. Algorithms should use parameters in combination (e.g., distance, TTC, turn signal use) to distinguish between lane change events and straight-ahead driving events.

Observed Data Values for Lane Changes and Straight-Ahead Driving (F = Forward, R = Rear)

	FDist	FTTC	RDist	RTTC	Brake	sig_on	sig_timing	Accel	Eye Glance
Unit	feet	seconds	feet	seconds	%	%	s +/- t ₀	ft/s ²	proportion
Lane Changes									F, RVM, LM
Avg	109.4	18.4	135.3	35.1	4.2%	64.0%	-0.6	UNK	.99, .46, .50
SD	74.5	14.9	124.0	18.9	NA	NA	1.2	UNK	NA
Baseline Events									F, RVM, IC
Avg	235.0	51.3	219.0	41.0	2.5%	0.0%	NA	1.5	1.00, .23, .25
SD	95.0	14.1	121.7	20.3	NA	NA	NA	UNK	NA

Based on such parameters, logistic regression models were developed for discriminating between lane changes and straight-ahead events (Olsen, 2003). One model included forward distance and TTC, rearward distance and turn signal activation. Evaluation of the model indicated that the model performed quite well, $AFCCF = 0.93$ (analogous to R^2), in its ability to match with the existing data. The model was in the form:

$$\hat{y} = 9.62 - 0.01 * FDist - 0.15 * FTTC - 0.01 * RDist + 15.82 * Sig_on$$

Another model included the turn signal *timing* (not realistic while driving) and included the addition of the rearward TTC, brake status, and turn signal timing with an $AFCCF = 0.96$:

$$\hat{y} = 10.057 - 0.013 * FDist - 0.221 * FTTC - 0.010 * RDist + 0.023 * RTTC + 4.102 * Brake + 41.381 * Sig_tim$$

Although based largely upon static data, it is believed that these models could serve as the basis for an enhanced model. An enhanced model would use dynamic data, with the addition of eye glance, side-object, and acceleration/deceleration data, to predict when the lane change will begin, as well as when to issue a LCAS alert or warning.

Supporting Rationale: Time-to-collision is important because it combines the distance between vehicles and relative velocity into a single measure, reported in seconds. Distance data is required because TTC is insufficient. If TTC is low but the vehicle is far away, then this vehicle is likely not a threat. Talmadge et al. (1997) recommended a TTC of three seconds for issuing a warning, confirmed by Olsen (2003). Brake pedal usage is also likely to be important (Olsen, 2003). The TTC parameter does not account for vehicle acceleration (Smith, Najm & Glassco, 2002), so acceleration data should be used. Acceleration was estimated based upon models developed by Snare (2002) and data collected by Rakha, Snare, and Dion (2003). Acceleration probably varies between pre-lane change periods and straight-ahead driving. A predictive model

could use such data to improve model performance (Chovan et al., 1994; Olsen, 2003), if available. Turn signal data should be incorporated into algorithms, but not all drivers use signals before changing lanes (Lee, Olsen, & Wierwille, 2003; Olsen, 2003; Hetrick, 1997). Real-time eye glance data should also be used (Tijerina et al., 1997; Olsen, 2003). But, since unobtrusive, affordable eye monitoring systems have not yet been implemented, this data is currently not available. Side object detection data should also be included as an indicator of lane change likelihood.

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System Integration

Introduction: Lane change crash avoidance systems (LCAS) should be integrated with other CAS and other vehicle systems. The purpose and manner of integration with LCAS are listed.

System Name	System Purpose and Scope	How Integrated
Lane Keeping/Run-off-the-Road Systems	Systems that assist drivers in maintaining lane position to avoid run-off-the road incidents, or to alert drivers when they are near the lane border	Uses similar sensors and displays
Enhanced Turn Signal System	An enhanced turn signal-activated system would only engage when conditions are safe. These systems might be based on the current turn signal activators and would issue warnings as needed. Visual display might be an enhancement of current turn signal displays with various arrow colors, sounds, etc.	Advance-ment of familiar system
ACC and Forward CAS	LCAS data could be integrated with both automatic cruise control (ACC) systems and forward CAS so that displays, sensors, and timing are compatible. Data from current and proposed research could be used with forward CAS.	Use displays that are distinct & coordinated
Eye Glance Monitoring.	Monitoring the glance patterns while driving is feasible using an unobtrusive system. This system could also work as a fatigue monitoring device based on PERCLOS.	2 Purposes: intention and fatigue
Lane Change Auto-Pilot	An advanced LCAS would operate analogous to an ACC system; when the system is active, it would automatically make smooth, safe lane changes using braking, acceleration, and steering.	Next step beyond LCAS
Driver Assessment	Driving assessment would be offered periodically based on actual driver data. Relevant and interesting data is summarized and reported to the driver in a customized format; this data might include velocity, following distance, fuel consumption, lane change rate, turn signal usage, and “close-call” data.	Part of larger system including lane position
Workload Management	A workload management system would monitor the driver so that a particular workload is never surpassed. If a driver is in dense traffic, is about to make a lane change, and a phone call is received, the system would hold the call until the driver is in a less stressful situation.	Would include lane position status
Vehicle-to-Vehicle/Device Communication	In the future, vehicles will share information with other vehicles/devices about their vehicle, traffic, road condition, traffic control devices. Radio transmission technology will deliver messages rapidly (i.e. using DSRC radio transmission technology)	Comple-ment to turn signal information
Use for Data Collection Efforts	Other data collection efforts (e.g., the 100-car study) could search archived data to understand thresholds or triggers that drivers typically exhibit while driving and as the basis for flagging near-miss or collision events. Specific parameter distributions would be used for identifying events. Data could be reviewed to understand typical parameters.	Provide further/ validation data to enhance LCAS

Supporting Rationale: Systems are being developed to assist drivers in maintaining lane position to avoid run-off-the road incidents or to alert drivers when they are near the lane border (Antonello, Vivo, & Burzio, 1995; Bertozzi & Broggi, 1998; Ledford, 2003) by using cameras to detect lane lines as a road lane monitoring system. Alerts can then be issued as an auditory tone (Antonello, Vivo, & Burzio, 1995) or as an earcon such as a virtual rumble strip (Ledford, 2003), when the car is near the lane border. Future systems might include variable resistance steering (Chovan et al., 1994) or automated vehicle control for maintaining lane position or making lane changes. This follows the concept of “auto pilot” for airplane landing descents. Current turn signal systems could be expanded to include the ability to engage only when conditions are safe. In order for warnings, displays, and controls to be compatible, lane change systems should be integrated with ACC and forward collision CAS to share relevant data. Eye glance monitoring while driving may be feasible using an unobtrusive system, similar to that used by Recarte and Nunes (2000; 2003). Such a system could measure eye glance movements, an indicator of lane change performance. Additionally, this same system could measure PERCLOS to detect drowsiness (Grace et al., 2001) as part of a driver monitoring system. Driver assessment would allow drivers to receive feedback on driving performance in conjunction with a driver workload management system such as the onboard information manager recently introduced by Chrysler called the “Driver Advocate” (Buchholtz, 2003). Vehicles may soon be able to share information with other vehicles and devices by using Dedicated Short Range Communications (DSRC) radio transmission technology (Kelly and Johnson, 2002). Archived data and resultant findings should be well publicized so that other data collection efforts can learn from previous efforts.

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APPENDICES

Commuters WANTED

WHO: Drivers who commute 25 miles or more each way on U.S. 460 and U.S. 11 (can be combined) or I-81.

Drivers must not ordinarily carpool or wear sunglasses while commuting.

WHAT: Participate in a study of drivers for approximately \$200.

QUALIFICATIONS: You must be healthy, have a good driving record, and drive most working days to work.

DETAILS: The Virginia Tech Transportation Institute in Blacksburg is conducting a study of commuter drivers using instrumented vehicles. Participants will drive our vehicles to and from work for four weeks. After two weeks, a different vehicle will be driven. This research is being sponsored by the National Highway Traffic Safety Administration and the Federal Highway Administration.

**For more information contact Erik Olsen at:
(800) 997-7836 or (540) 231-1500**

Driver Study: Contact Erik Olsen at 231-1500 or 800-997-7836	Driver Study: Contact Erik Olsen at 231-1500 or 800-997-7836	Driver Study: Contact Erik Olsen at 231-1500 or 800-997-7836	Driver Study: Contact Erik Olsen at 231-1500 or 800-997-7836	Driver Study: Contact Erik Olsen at 231-1500 or 800-997-7836	Driver Study: Contact Erik Olsen at 231-1500 or 800-997-7836	Driver Study: Contact Erik Olsen at 231-1500 or 800-997-7836	Driver Study: Contact Erik Olsen at 231-1500 or 800-997-7836	Driver Study: Contact Erik Olsen at 231-1500 or 800-997-7836	Driver Study: Contact Erik Olsen at 231-1500 or 800-997-7836
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Appendix B: Telephone Driver Screening and Demographic Questionnaire.

Driver Screening and Demographic Questionnaire

Date _____

Good day. My name is Erik Olsen and I am a researcher with the Virginia Tech Transportation Institute in Blacksburg, VA. The project is a driving study with commuter drivers using instrumented vehicles.

This study will involve you driving a car and then a SUV or vice versa for two weeks each as you commute to and from work. Each vehicle will be equipped with data collection equipment. All data shall only be used by VTTI researchers. Does this sound interesting to you?

Next, I would like to ask you several questions to see if you are eligible to participate. If there is a question you are uncomfortable with, you do not have to answer it.

Name: _____ Gender: MALE FEMALE
Address: _____
Home Phone: _____ Work Phone: _____ BTTC _____

1. In what age bracket are you? (must be between 20 and 65 years old)

- 20-29 _____
- 30-39 _____
- 40-49 _____
- 50-59 _____
- ≥ 60 _____

2. Do you have any health conditions or physical disabilities, including but not limited to night blindness, sleep disorders, or diabetes that affect your ability to drive safely?

Yes _____ No _____ If yes, what are they? _____

3. Do you have a valid driver's license? Yes _____ No _____

4. How long have you been driving? _____

5. What is the make, model, and year of the car you currently drive? _____

6. Do you drive to work each day? Yes _____ No _____ What days? _____

7. Do you normally drive to/from work alone? Yes _____ No _____

8. What is the specific route with mileage that you drive to/from work?

9. Have you had any moving violations in the past 3 years? If so, please explain.

Yes _____ No _____

10. Have you been involved in any accidents within the past 3 years? If so, please explain.

Yes _____ No _____

11. Have you had any DUI convictions? Yes _____ No _____ (Must not have any)

12. Do you have car insurance? Yes _____ No _____

13. Do you ordinarily wear prescription glasses while you drive? Yes _____ No _____
How about sun glasses? Yes _____ No _____

14. Would you be willing and able to drive without wearing sunglasses during the time you are driving our vehicles? Yes _____ No _____

15. Have you previously participated in any experiments at the Virginia Tech Transportation Institute? If so, can you briefly describe the study? Yes _____ No _____

16. (Females only) Are you currently pregnant? Yes _____ No _____
If yes, when are you expecting? _____

17. This study will involve your using our vehicles to commute to and from work. Do you have a convenient, safe place to keep the vehicle at home? (e.g., garage, driveway, street)

Thank you for answering these questions. At this time you are/are not considered eligible for our study. (If eligible): At this time I anticipate that we will have you start the study on _____. The next step is to schedule an orientation meeting. How does _____ work for you?

(If not eligible): At this time for _____ reason, it appears that you are not eligible for this study. Thank you for your time.

Appendix C: Informed Consent Form.

INFORMED CONSENT FORM FOR PARTICIPANTS

NATURALISTIC HIGHWAY DATA GATHERING STUDY

Investigators: Walter Wierwille, Thomas Dingus, and Erik Olsen

I. THE PURPOSE OF THIS RESEARCH

The purpose of this research is to gather naturalistic data on ordinary drivers using instrumented vehicles. Most data are gathered with an experimenter present in the vehicle, which may lead to driving behavior that differs substantially from the way drivers drive under ordinary circumstances. Naturalistic data are needed as a foundation for new driver support systems, such as collision warning and avoidance systems. Unless such data are available, it is difficult to determine how best to design such systems in a way which optimizes the driver/vehicle interface.

II. PROCEDURES

You are being asked to drive each of two instrumented vehicles in your daily commute to work. These vehicles contain sensors and data processing that can capture your normal driving. Small video cameras are also mounted in the vehicle. One of these cameras will be directed toward your face while you are driving. The equipment has been installed in such a way that you will hardly be able to notice its presence. It will not interfere with your driving, and there is nothing special that you will need to do in regard to the equipment.

One of the vehicles is a Ford Taurus and the other is a Ford Explorer. Each vehicle will be lent to you for a period of approximately two weeks and is to be substituted for the vehicle you would ordinarily drive back and forth to work. We ask you not to drive the research vehicles at other times, unless you have an emergency.

We would like to take a drive with you to familiarize you with the handling and layout of the Explorer. This is done as a safety precaution. Similarly, we would like to take a familiarization drive with you in the Taurus.

As a participant in this study, you are requested to perform the following duties:

1. Carefully read this informed consent form and then sign it if you agree to participate.
2. Fill out a driver questionnaire, which requests information on your health, the type of vehicle you most often drive, and additional information, such as how long you have been driving. (Assuming that your responses meet our criteria for participation, we will attempt to schedule you for full participation.)
3. Receive instruction and take on-the-road test drives in the Explorer and the Taurus.
4. Drive as you ordinarily would on your trips back and forth to work. The only difference is the vehicle you would drive. You need not “perform”. Just drive as you ordinarily would.
5. Keep the vehicle provided to you locked when not in use, preferably in a reasonably secure place. Try to maintain reasonable security for the vehicle while it is in your possession.
6. Participate in two different portions of the study. In one portion, you will drive one of the vehicles (either the Taurus or the Explorer) to work for about two weeks. Later, you will drive the other vehicle for about two weeks. In some cases there may be an interval of time between the two sessions.
7. Drive by yourself back and forth to work. We are particularly interested in single- occupant driving, so you are requested not to carry passengers except in an emergency.
8. Fill out a post-drive questionnaire regarding your participation. You will do this one time at the end of your participation.

III. RISKS AND DISCOMFORTS

There are some minor risks to which you will be exposed in participating in this experiment. Known risks are listed here.

1. There is the risk of an accident resulting from your driving back and forth to work. This risk is the same as you face in the vehicle you ordinarily drive.
2. There is the slight additional risk of an accident resulting from driving a vehicle less familiar to you than your everyday vehicle. This additional risk is roughly equivalent to borrowing or renting a car or an SUV for your commute back and forth to work. This risk is expected to subside as you become familiar with each of the research vehicles used in this experiment.

The following precautions will be taken to ensure that risks are minimized:

1. You agree to use the seat belt and shoulder strap restraint in the vehicle whenever the vehicle is in motion.
2. The two vehicles used in this experiment are modern vehicles with airbags and other safety equipment found on newer vehicles.

3. All of the data gathering equipment will be secured in the vehicle so that it does not present a hazard. The equipment will not obstruct your view out the windows or through the rear-view mirrors. The equipment will also be unobtrusive.

4. You will be given instruction and test drives in both the Explorer and the Taurus to help familiarize you with these vehicles.

IV. BENEFITS TO YOU

You will be paid a gratuity for your participation and you will also have vehicles provided for your commute to and from work for approximately four weeks in total. You will also be reimbursed for the approximate cost of gasoline used during your commuting in the vehicles provided. There are no other known direct benefits to you. No promises or guarantee of benefits other than those listed in this informed consent form have been made to encourage you to participate. You may however enjoy driving the research vehicles, and it is likely that your participation in this experiment will help provide a better understanding of naturalistic driving behavior and how future safety improvements might be developed.

V. EXTENT OF ANONYMITY AND CONFIDENTIALITY

The information gathered in this experiment will be treated with confidentiality. It will be used for research purposes only, and only by qualified researchers. Your name and other identifiers will be removed from the overall data set and in any resulting publications.

As indicated, video will be recorded while you are driving. The video includes an image of your face, so that we can determine where you are normally looking. The video will be treated with confidentiality and kept secure. It will be shared only with other qualified researchers, and not published except as noted in the following paragraph.

If at a later time we wish to use the video information for other than research purposes, say, for public education, or if we wish to publish (for research or for other purposes) your likeness or other information from the study that identifies you either directly or indirectly, we will only do so after we have obtained your permission.

Your data will be pooled with that of at least eight other participants. (The expected number of participants is likely to be between twelve and sixteen.)

VI. COMPENSATION

You will receive a gratuity for participating in this experiment. For each day in which you commute to work in one of the instrumented vehicles, you will receive \$10. If you save your receipts for gas, you will be reimbursed for the amounts spent. Therefore, under ordinary circumstances, if you complete the experiment, you will receive \$200, that is, \$10 times 20 days. Reimbursement for gas will be added to this amount. You will receive payment of your gratuity at the end of your participation. Reimbursement for gas will also be made at that time.

It is possible that a data gathering equipment malfunction may occur during some portion of your participation. If this should occur, we may have to temporarily suspend the experiment to service the data gathering equipment. While the equipment is out of service, you will be paid \$4 per commuting day and you will have to use your regular vehicle. You may then be asked to extend your participation for an extra day or two, or possibly more to make up for the equipment problem. If you choose to do so, you will be paid an additional \$10 for each additional commuting day of participation in which you drive one of the instrumented vehicles.

VII. MEDICAL TREATMENT AND INSURANCE

If you should become injured in an accident, the medical treatment available to you would be that provided to any driver or passenger by emergency medical services in the vicinity where the accident occurs.

The vehicle you will be driving is insured for automobile liability and collision/comprehensive through Virginia Tech and the Commonwealth of Virginia. There is medical coverage for you under this policy. The total policy amount per occurrence is \$2,000,000. This coverage would apply in case of an accident, except as noted below.

Under certain circumstances, you may be deemed to be driving in the course of your employment, and your employer's worker's compensation provisions may apply in lieu of the Virginia Tech and Commonwealth of Virginia insurance provisions, in case of an accident. The particular circumstances under which worker's compensation would apply are specified in Virginia law. If worker's compensation provisions do not apply in a particular situation, the Virginia Tech and Commonwealth of Virginia insurance provisions will provide coverage.

A Virginia Tech automobile accident report form is located in the glove compartment of the vehicle you will be driving and outlines what you should do if you become involved in an accident and are not incapacitated.

VIII. FREEDOM TO WITHDRAW

As a participant in this research, you are free to withdraw at any time without penalty. If you choose to withdraw, you will be compensated in accordance with the terms in Section VI. of this document.

IX. APPROVAL OF THIS RESEARCH

Before this experiment begins, the research must be approved by the Institutional Review Board for research involving human subjects at Virginia Tech as well as the sponsor's human use review panel. You should know these approvals have been obtained.

X. PARTICIPANT’S RESPONSIBILITIES

If you voluntarily agree to participate in this study, you will have the following responsibilities while driving the research vehicles:

- 1. To be free of any illegal substances and to refrain from the use of alcohol and other substances that may impair your driving ability,
- 2. To conform to the laws and regulations of driving on public roadways,
- 3. To drive as you ordinarily would, but subject to 1. and 2. above,
- 4. To wear your seatbelt at all times while driving the vehicle,
- 5. To maintain reasonable security of the research vehicle in your possession,
- 6. To allow the experimenters to gain reasonable access to the research vehicle in your possession for purposes of diagnosing difficulties and downloading data, and,
- 7. To inform one of the experimenters if you encounter difficulties or have questions.

XI. PARTICIPANT’S PERMISSION

I have read and understand this informed consent form and conditions of my participation. I have had all my questions answered. I hereby acknowledge the above and give my voluntary consent to participate.

If I participate, I understand that I may withdraw at any time without penalty. I agree to abide by the rules of this project.

Participant’s Signature

Date

Should I have any questions about this research or its conduct, I may contact:

- Walter Wierwille, Project Principal Investigator (540) 231-1500
- Thomas Dingus, Director, Virginia Tech (540) 231-1500
Transportation Institute
- Erik Olsen, Graduate Research Assistant (540) 231-1500
- David Moore, Chairman, Institutional Review Board (540) 231-4991

Appendix D: Driving a Sport Utility Vehicle (SUV).

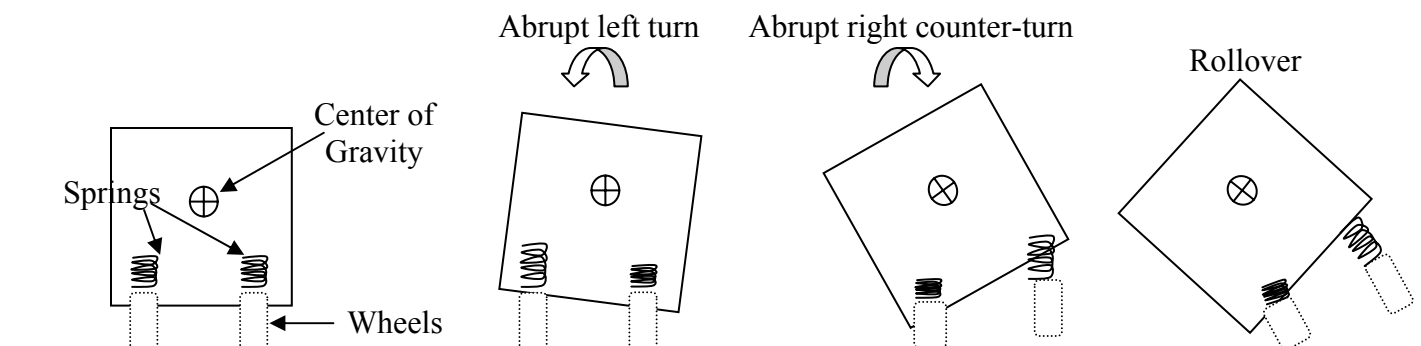
During this study, one of the vehicles you will be driving is a SUV. The SUV you will be driving is a Ford Explorer. This vehicle, as is the case with many SUVs, has a high center of gravity and is more unstable than a typical passenger car. Therefore this SUV has a significantly higher rollover rate than other types of vehicles.

Vehicles with a higher center of gravity handle differently than vehicles with a lower center of gravity. A SUV is not designed for cornering at speeds as high as those that are typical of most passenger cars. Avoid sharp turns, excessive speed, and abrupt maneuvers in this vehicle.

Another factor leading to rollover, is the "loading" of the suspension system during an evasive maneuver. SUVs have been made safer by stiffening the suspension. In other words, the springs have been made harder and the vehicle becomes more roll resistant. However, during an abrupt maneuver or turn, it is possible to load these springs, which, in combination with the high center of gravity, can also contribute to vehicle rollover.

The chief hazard occurs when taking emergency action (an abrupt turn) after steering in one direction and then being forced to rapidly correct in the opposite direction (a counter-turn). The result can be a rollover. Rollover occurs because of the absence of a lower center of gravity and a wider track width, which allows automobiles to skid, spin and recover. For a SUV, when making a common evasive maneuver that car drivers safely complete every day, rapid corrective action may cause a SUV to catch its wheels or "trip" and rollover.

The figure below illustrates that these two factors, high center of gravity and spring loading, can lead to a rollover if abrupt maneuvers are made.



In this hypothetical case, an abrupt left turn was made to avoid an object on the road. The driver then made an abrupt right turn to counter the original maneuver and the vehicle began to rollover.

To visualize this more clearly you will now be shown a short demonstration video.

Appendix E: Analyst Training Manual.

Naturalistic Lane Change Field Data Reduction, Analysis, and Archiving

Definitions and Graphical Depictions of Lane Change Categories (Severity, Type, Success, and Magnitude) August 1, 2001

The following material was used in reviewing the entire set of all lane changes/passing events collected during data collection. Note that some of the information here was changed after all events were identified (e.g., the rating scales were changed to the severity and urgency scales; some of the classifications were changed).

Video Tape Labeling Conventions

All video tapes are labeled with Project Name, Subject and Tape Number, Research Vehicle, Route Driven, Driver's Normal Vehicle, Begin Date (when data collection began for that tape), and Researcher's Name. Figure I-1 illustrates the tape labeling conventions used for the video tape labels.

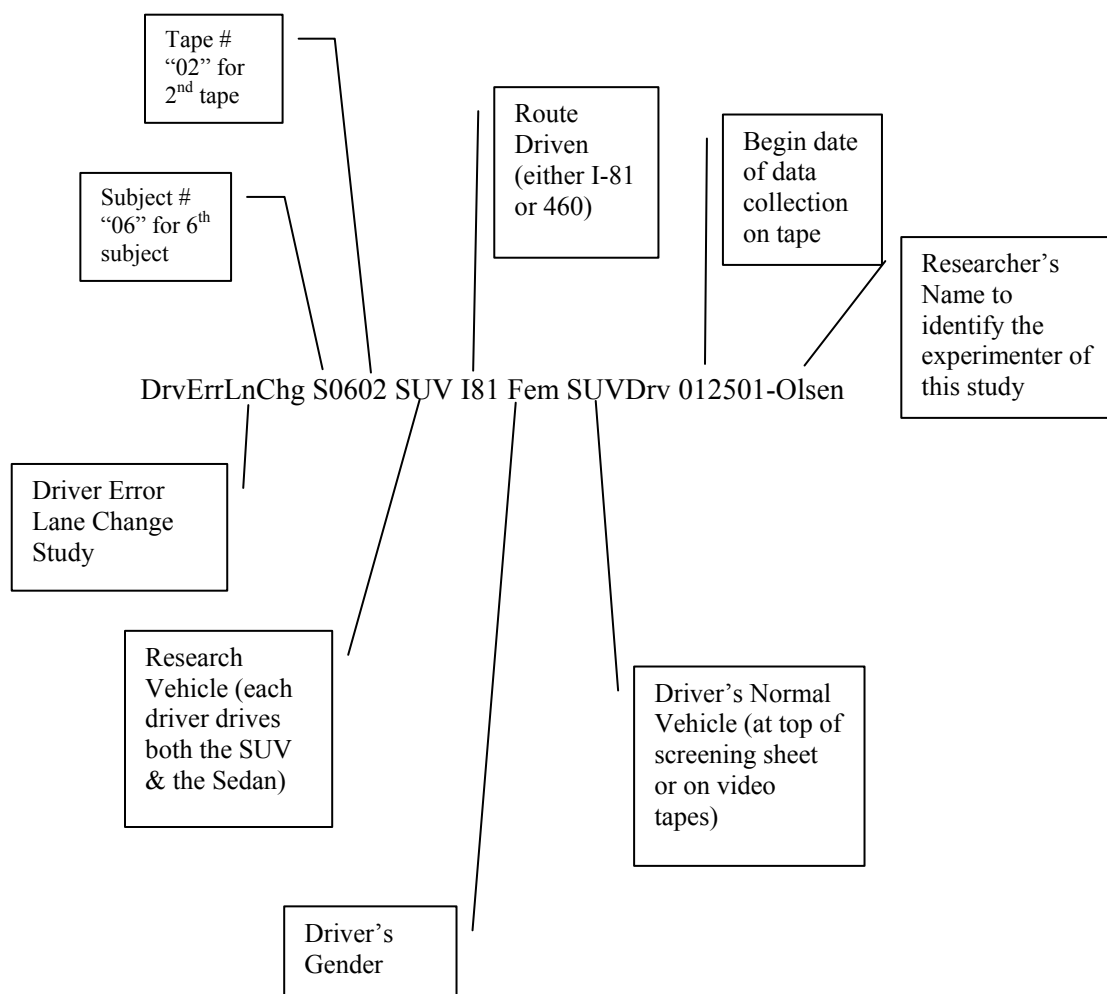


Figure I-1. Video Tape Labeling Conventions.

Zip Disk Labeling Conventions

All zip disks are labeled with Project Name, Subject Number, Research Vehicle, Route Driven, Gender, Driver's Normal Vehicle, Begin Date and End Date (when data collection began/ended for that zip), and Researcher's Name. Figure I-2 illustrates the zip labeling conventions used for the zip disk labels.

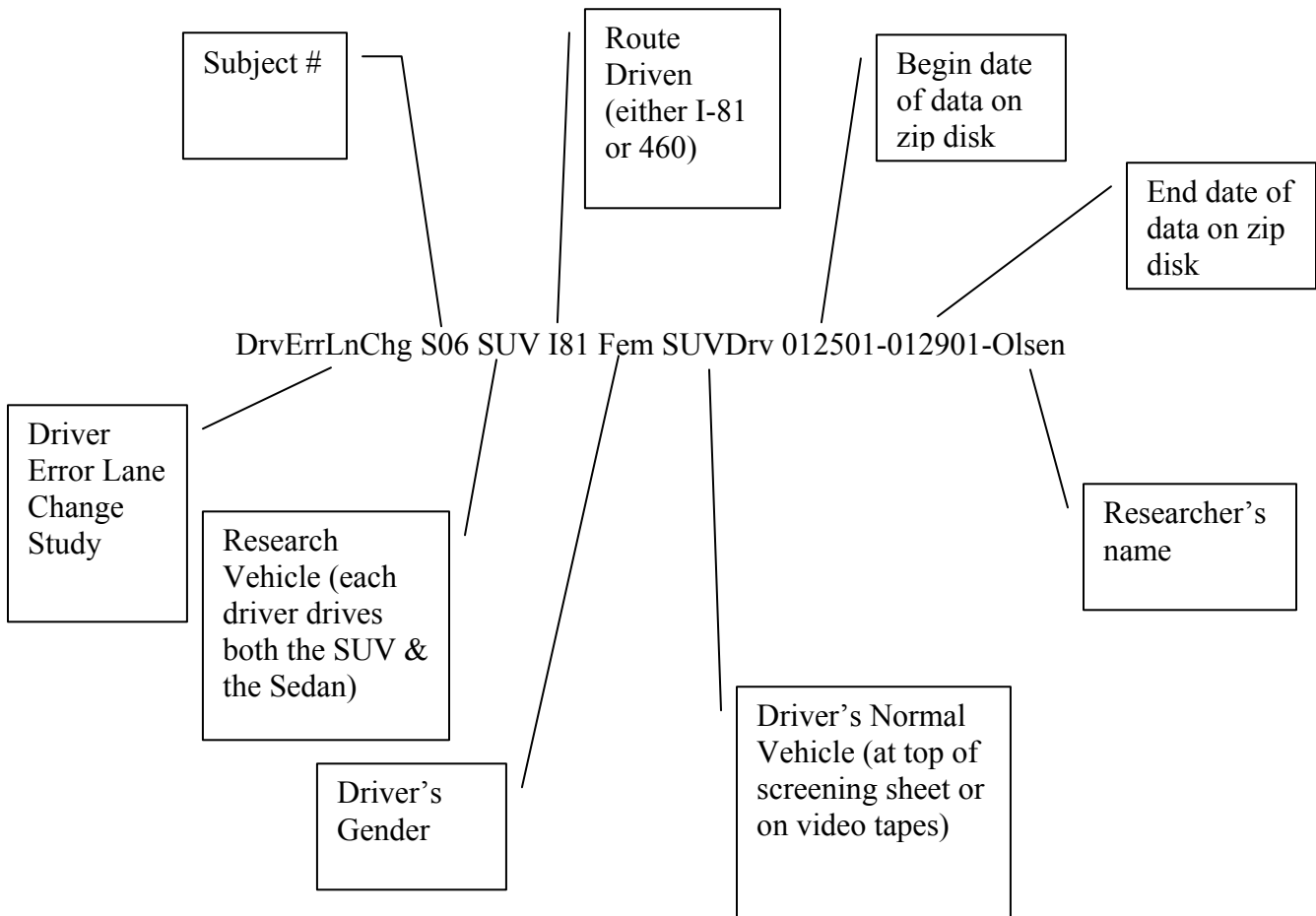


Figure I-2. Zip Disk Labeling Conventions.

Lane Change Start and End Points

In terms of video analysis, a lane change will be considered to start when it is obvious on the videotape that the driver has begun steering into the lane change. This can usually be seen quite easily using the lower right hand quadrant of the video, which shows the right and left rear views. As the driver makes the initial steering move, the center line and side markers, which have been stable in the image, will begin to shift to one side or the other. With practice, multiple reviewers can learn to pinpoint this frame of the videotape within 0.1 seconds of one another.

The lane change will be considered to have ended at the point at which the driver has settled into the new lane. This can usually be seen using the lower right hand quadrant of the video, which shows the right and left rear views. As the driver settles, the center line and side markers, which

have been steadily changing, will settle into a stable pattern. Sometimes the driver will overcompensate and then steer back to settle into the new lane. In this case, the lane change ends after the overcompensation correction ends and the driver is settled into the new lane. Watching the videotape in real time will allow the analyst to see when this is happening. Occasionally when a driver is passing a slower vehicle (especially a truck), he or she will hug the outside road marker while passing and then settle into the center of the lane. If a driver appears to be doing this, the lane change will be considered to have ended when the driver is settled into the "edge of the road" pattern (in other words, do not continue the lane change all the way through the "edge of the road" phenomenon until the point where the driver shifts back into the center of the new lane after passing). For a passing maneuver (lasting less than 45 seconds), the lane change will be considered to have ended when the subject vehicle is settled back into its original lane.

If there are any questions about lane change start and end points, ask one of the senior researchers. Note that there is some natural variation in how abruptly lane changes begin and end, even with the same driver. For a lane change which is gradual, the movement of the center and side markers is not always obvious, especially when viewing the tape in slow motion.

Duration

For each event identified, the duration will be calculated. For example, when entering data into the Excel spreadsheet, a duration column exists where the End synch number is subtracted from the Begin synch number for that event and then divided by 10 (e.g., Duration =(F2-E2)/10. This results in a value in seconds.

Road Type

- Interstate (i) I-81 or I-581
- US hwy (us) US460 or US11
- Other (o) Passing maneuver on any other road type, mark for future decision

Subjects who drive on one type of road for the majority of their commute may drive on another type for a short part of the commute. Try to classify each lane change into the correct category.

Direction of Maneuver

- Right (r) Driver moves from the left to the right
- Left (l) Driver moves from the right to the left

Success/Magnitude Categories

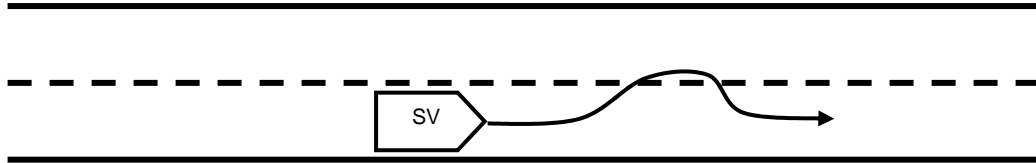
All events will be categorized in one of the following categories:

Category	Definition
Single (s)	Single lane change, ends in adjacent lane (by definition, successful).
Multi (m)	Multiple lane change, does not end in original lane or adjacent lane (by definition, successful).
Pass (p)	Dual lane change/passing maneuver, ends in original lane, ≤ 45 seconds duration (by definition, successful).
Partial (u)	Lane change that was not completed (by definition, unsuccessful).

Graphic Definitions for Lane Change Success/Magnitude

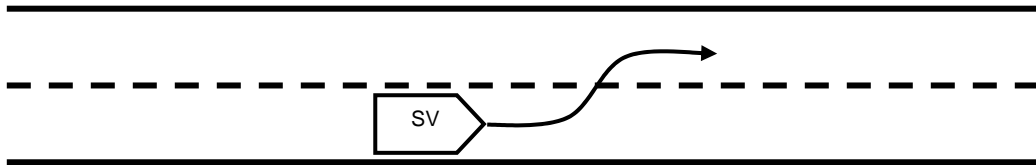
Classification name: partial (U for “unsuccessful”)

Classification definition: Subject vehicle reverts to original lane before completing lane change (SV never settles in new lane). The presence or absence of POVs is irrelevant to this classification scheme.



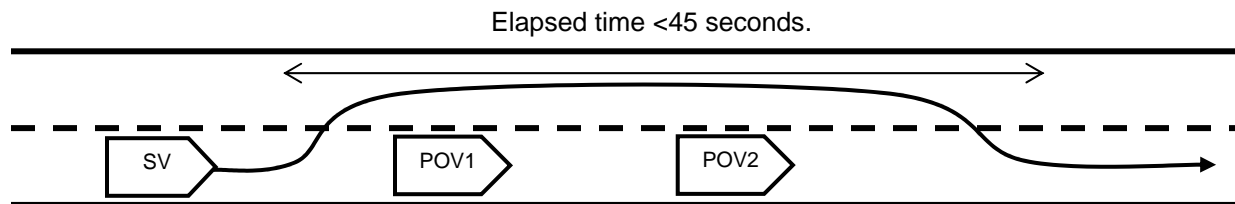
Classification name: single (S)

Classification definition: The SV changes lanes and settles in an adjacent lane. The presence or absence of POVs is irrelevant to this classification scheme.



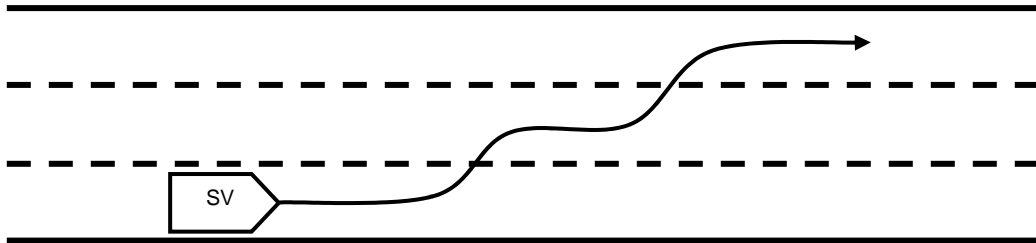
Classification name: pass (P)

Classification definition: The SV changes lanes and reverts back to the original lane within 45 seconds. Most often this maneuver is due to slow POVs ahead, and the SV will pass one or more of these POVs during the course of the passing maneuver.



Classification name: multi (M)

Classification definition: A multiple lane change in which the SV does not end up in the original lane (as opposed to a passing maneuver, in which the SV returns to the original lane). The presence or absence of POVs is irrelevant to this classification scheme.



Notes

A column for notes exists to allow notation of unexpected events or question for later review.

Lane Change Type Classifications (Revised 7/31/01)

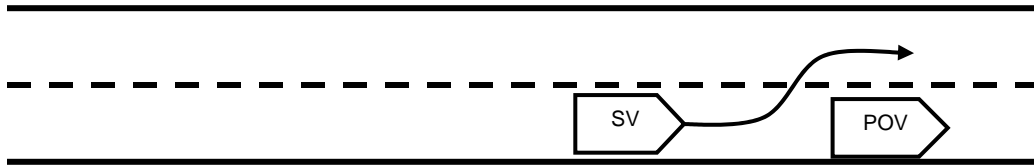
Lane Change Types

LC Type	Description
Slow lead veh	Lane change to pass a vehicle which is moving slower than the SV's preferred speed.
Return	Lane change to return to preferred driving lane.
Enter	Lane change to enter road (e.g., from on-ramp).
Exit/prep exit	Lane change associated with exiting.
Tailgated	Vehicle tailgating/approaching quickly.
Merging veh	Vehicle entering roadway causing SV to change lanes.
Rough/obst avoid	Maneuver to avoid obstacle or rough road surface.
Lane drop	End of driver's lane (e.g., road goes from 3 to 2 lanes).
Added lane	Addition of a lane (e.g., road goes from 2 to 3 lanes).
Unintended	Unintended lane deviation (e.g., distraction in car).
Other	Lane change for any other reason or for no discernible reason.

Graphic definitions for lane change types (not updated to reflected 7/31 changes from Table above)

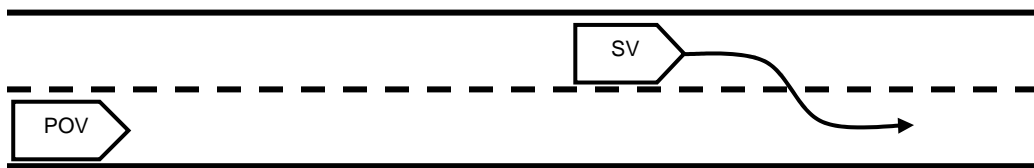
Classification name: slow lead vehicle

Classification definition: Lane change due to slow principal other vehicle (POV) in front.



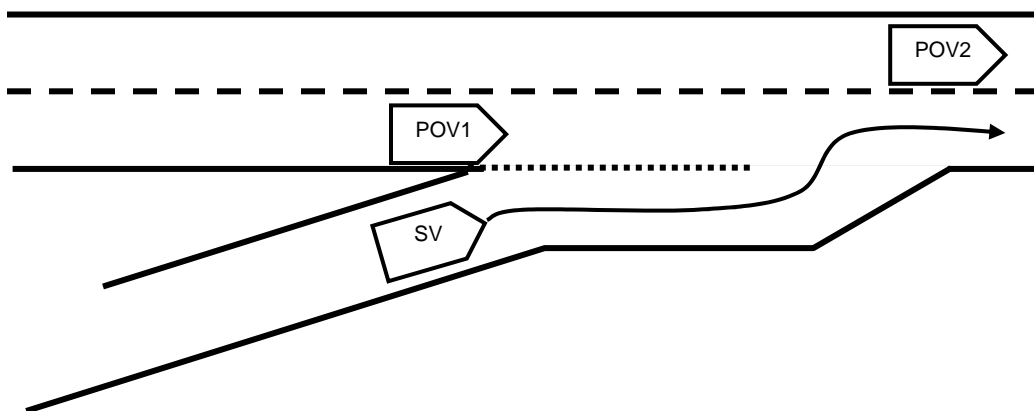
Classification name: return

Classification definition: Lane change to return to original lane after deviating from it for any reason.



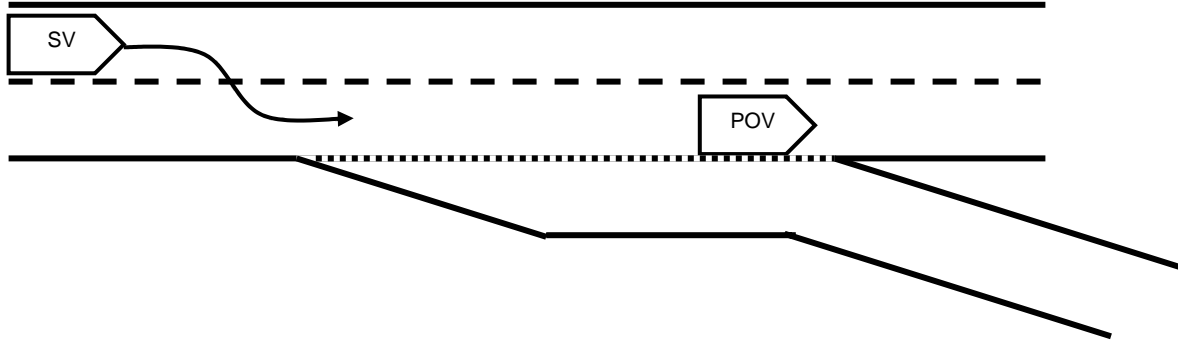
Classification name: enter

Classification definition: Lane change to enter the main highway. The TTC to POVs already on the highway are accounted for in the severity ratings.



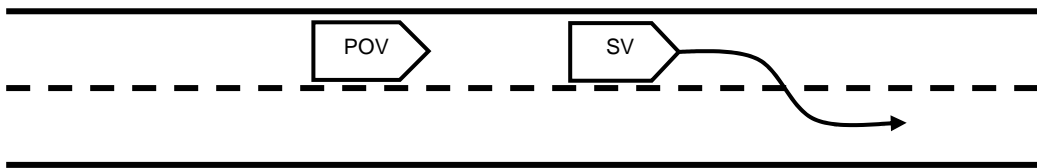
Classification name: exit/prep exit

Classification definition: Lane change to exit or to prepare to exit the main highway. The TTC to POVs are accounted for in the severity ratings.



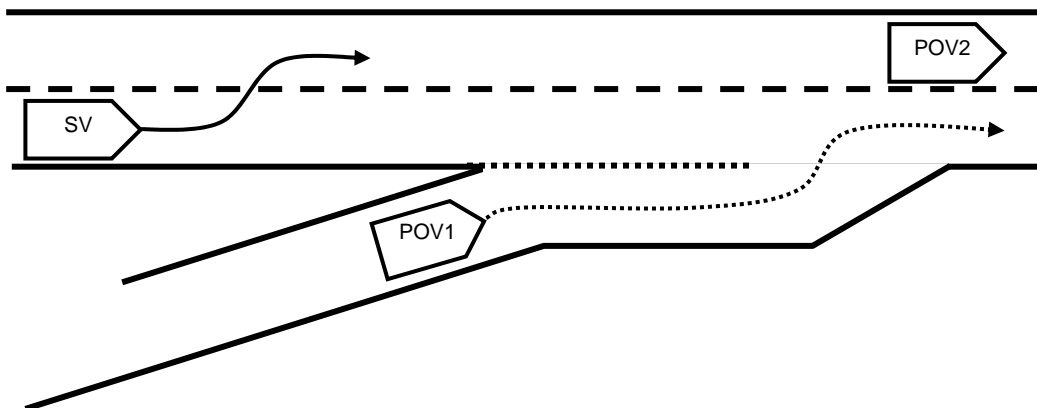
Classification name: tailgated

Classification definition: Lane change due to POV tailgating/approaching quickly; usually occurs while in the left lane. Driver of SV may make lane change while POV is still at a considerable distance/TTC. If, in the analyst's judgment, this is the true reason for the lane change, use this classification rather than any of the returning to original lane classifications. The TTC to POVs are accounted for in the severity ratings.



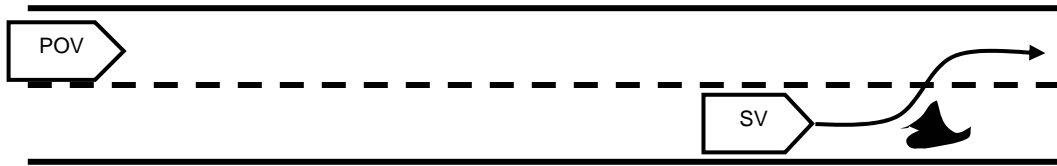
Classification name: merging veh

Classification definition: Lane change to allow POV to enter the main highway. The TTC to POVs are accounted for in the severity ratings.



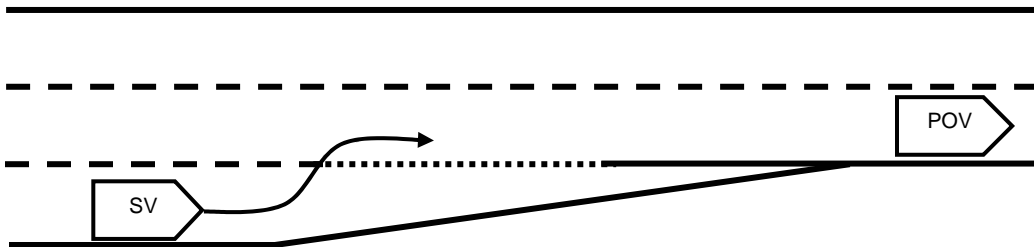
Classification name: rough/obstacle avoidance

Classification definition: Lane change due to road surface or obstacle in road. The TTC to POVs are accounted for in the severity ratings.



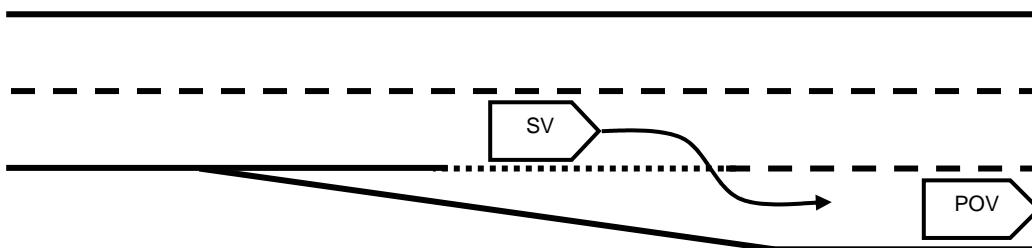
Classification name: lane drop

Classification definition: Lane change due to end of SV's lane (e.g., road goes from 3 to 2 lanes). The TTC to POVs are accounted for in the severity ratings.



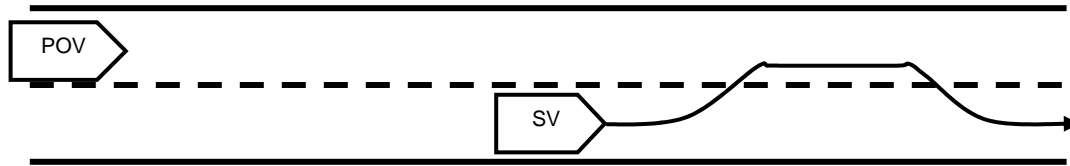
Classification name: added lane

Classification definition: Lane change due to the addition of a lane (e.g., road goes from 2 to 3 lanes). The TTC to POVs are accounted for in the severity ratings.



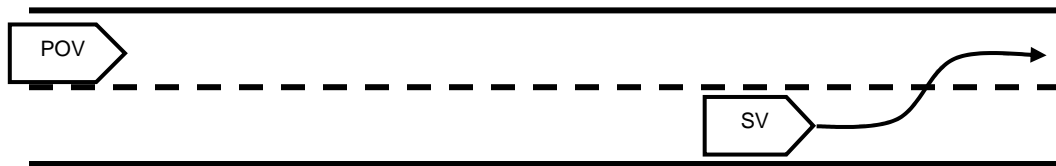
Classification name: unintended

Classification definition: Unintended lane deviation due to distraction, drowsiness, poor driving, etc.; often only a partial lane change. The TTC to POVs are accounted for in the severity ratings.



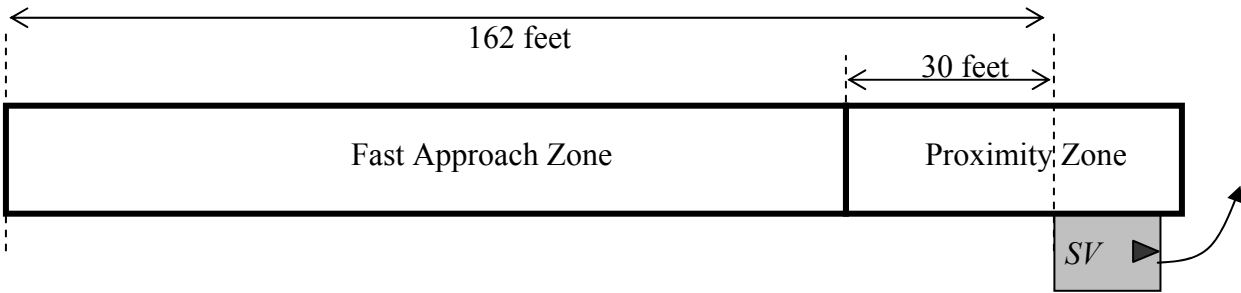
Classification name: other

Classification definition: Lane change for no discernible reason. The TTC to POVs are accounted for in the severity ratings, and POVs can be in any lane position relative to the SV.



Conflict Severity Rating: A lane change conflict, by definition, requires that there be a vehicle present in the lane into which the driver of the SV wishes to move.

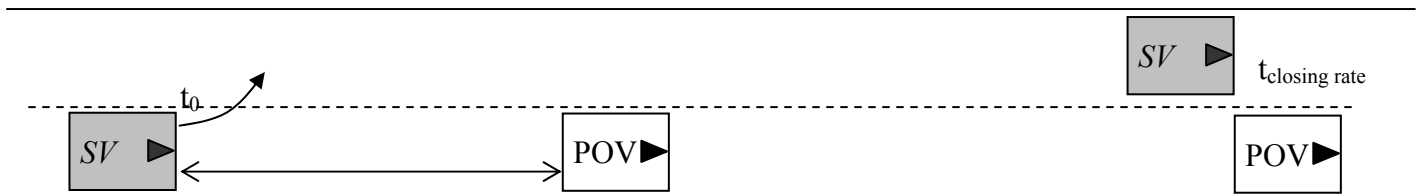
Rating	Description
7	Crash of any type
6	Emergency action/unplanned sudden maneuver required to avoid a collision with a vehicle (or object) in the adjacent lane into which the driver of the SV was attempting to move.
Ratings 5 through 1 are assessed at initiation (<u>Start Synchrony</u>) of the attempted lane change.	
5	POV in the proximity zone.
4	POV in the fast approach zone with time to reach closest end of zone, $T_r^\dagger \leq 1.0$ sec.
3	POV in the fast approach zone with time to reach closest end of zone in the range $1.0 < T_r \leq 3.0$ sec.
2	POV in the fast approach zone with time to reach closest end of zone in the range $3.0 < T_r \leq 5.0$ sec.
1	POV in the fast approach zone with time to reach closest end of zone, $T_r > 5.0$ sec, including case where there is no vehicle in the adjacent lane.



[†] T_r is the time required for a POV to reach the front end of the fast approach zone. (This point is 30 ft behind the SV.)

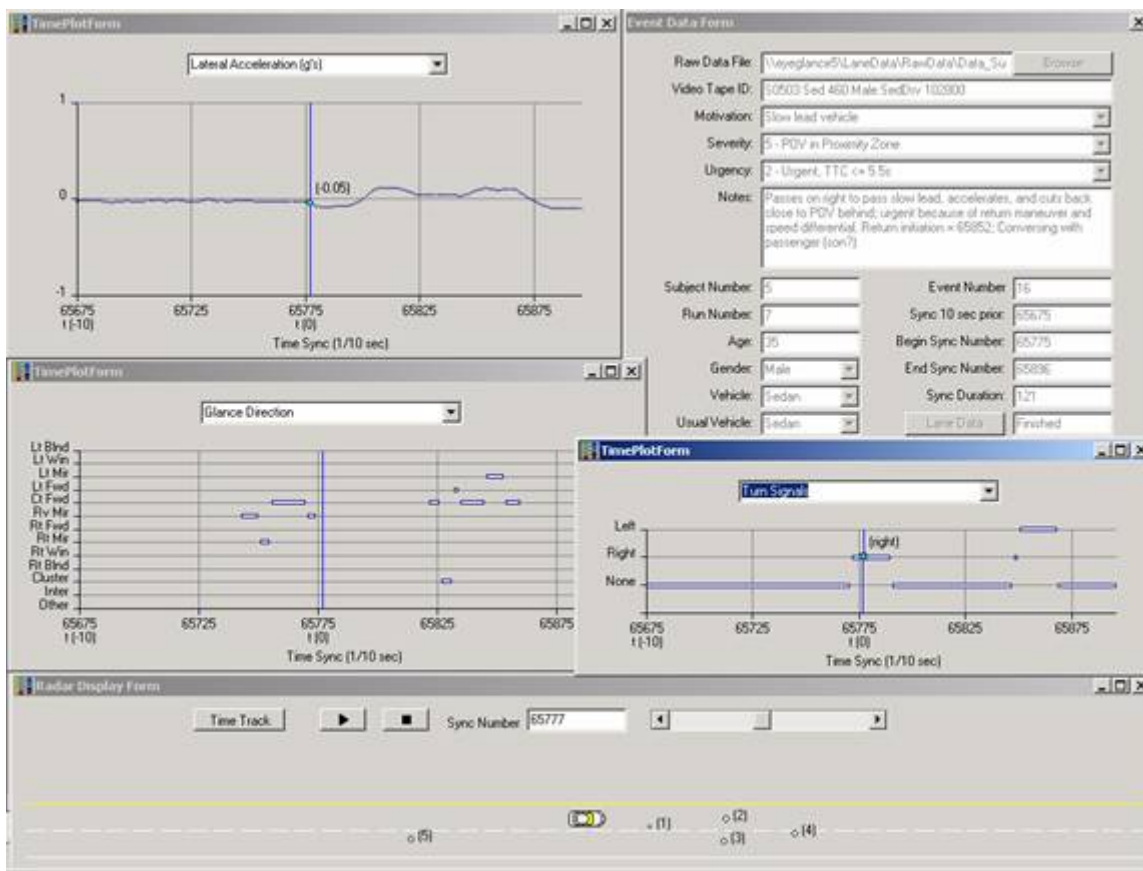
Urgency Rating: Each type classification can be placed in one of the following categories, according to the urgency of the SV's relationship to vehicle(s) in same lane or opposite adjacent lane (the lane opposite the one into which the SV intends to move):

Rating	Description
4	<u>Critical incident/crash:</u> Physical contact/collision occurs with a vehicle (or object) in the same lane as the SV or the opposite adjacent lane; or a sudden maneuver (braking or swerving) is required to avoid such a collision.
3	<u>Forced:</u> The lane change has a high degree of urgency due to fast closing rate* ($TTC \leq 3s$) and/or close headway/tailway/distance to vehicle in the same or opposite adjacent lane.
2	<u>Urgent:</u> The lane change is somewhat urgent due to moderate closing rate ($5.5s \geq TTC > 3s$) and/or moderate headway/tailway/distance to vehicle in the same or opposite adjacent lane.
1	<u>Non-urgent:</u> The lane change is not urgent, because of a zero or negative closing rate ($TTC > 5.5 s$) with vehicle in the same or opposite adjacent lane, and/or long headway/tailway/distance, and/or lack of vehicles in the same or opposite adjacent lane.



* Closing rate between vehicles is the number of seconds (time) it would take for vehicles to collide if the rear vehicle did not maneuver. In other words, it is the time from the initiation (Start Synchrony) of the lane change to the time when the front bumper of the SV is parallel with the rear bumper of the POV (e.g., when the POV is in front of the SV).

Appendix F: User Manual for Lane Change Data Reduction Program.



May 1, 2002

Event Analysis Protocol Overview

This document explains how to view events using the Lane Change Data Reduction Program, as used to analyze the sample of 500 lane change events from the total database. This program was created by Brian Leeson of VTTI to allow analysts to identify and characterize lane changes collected from on-road vehicles. The data collected used three hardware systems. The hardware systems collected numerous data including eye behavior (i.e., allowing extraction of location and duration of eye glances prior to and during maneuvers), driver-vehicle performance measures (steering wheel behavior, number and average length of lane changes, vehicle velocity, and turn signal usage), and driving performance data related to lane-changing behavior (azimuth, gap, and gap closing rate to other vehicles fore and aft).

Considered separately, these data are difficult to interpret. For example, one could imagine attempting to use a spreadsheet to make sense of various data sources.

The Lane Change Data Reduction Program allows the analyst to gain insight as to what is taking place during a specific maneuver by integrating the three types of data. Such integration allows

the analyst to identify, review, categorize, and rate maneuvers. To assist in this task, a customized system was developed for review of all data types in conjunction with the composite video. The program can read raw data files consisting of radar and vehicle data for a desired lane change or passing event.

The following pages explain how to view events created by the program. It can be read without access to actual data files to gain a general understanding of how it works.

Running the Program

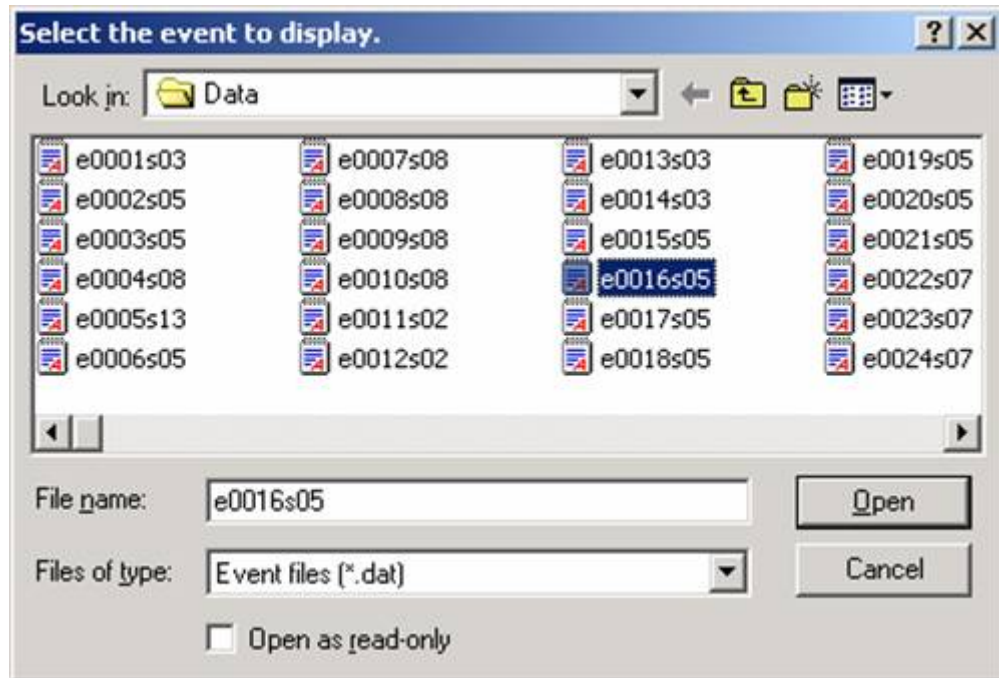
To allow the Lane Change Program to operate (to display analyzed events):

1. Place the Lane Change CD into the CD drive. The following directories and files exist:
 - “Data” contains .dat files created by the Lane Change Program (e.g., "e0001s03.dat"). Files include 0001 through 0517. Files 0034, 0114, 0141, 0146, 0148, 0197, 0259, 0262, 0276, 0277, 0283, 0308, 0361, 0413, 0421, 0424, 0430 are included but data were not available to fully analyze these events.
 - “Frames” is an empty directory required for the program to run.
 - “RawData” is empty, but exists to store subdirectories for each subject, e.g., "Data_Subject2"). These subdirectories are not required to display events. However, when data were originally entered, each subdirectory contains further subdirectories for that subject for each data collection session, e.g., "data_100500_0201_SUV" corresponding to data collected on October 5, 2000 for Subject#2, tape #1 in the SUV). Each of these subdirectories contained a series of .dat files created during data collection, e.g., "V002_01.dat" created on 10/5/00 at 9:40 AM corresponding to the first data collection run for that data collection session. **All that is needed to display these events are the data files in the "Data" directory, created by the Lane Change program when they were originally entered.**
 - borlndmm.dll (Application Extension)
 - cp3240mt.dll (Application Extension)
 - drwtsn32 (log file)
 - LaneChange (Application File)
 - Sedan (Horizontal Bitmap file)
 - Sedan2 (Vertical Bitmap file)
 - softdata.tmp (temp file)
 - SUV (Horizontal Bitmap file)
 - SUV2 (Vertical Bitmap file)
 - vcl35 (bpl file)
2. Run the LaneChange Program by clicking on the Lane Change Application icon within the LaneData directory on the CD.

Displaying Events

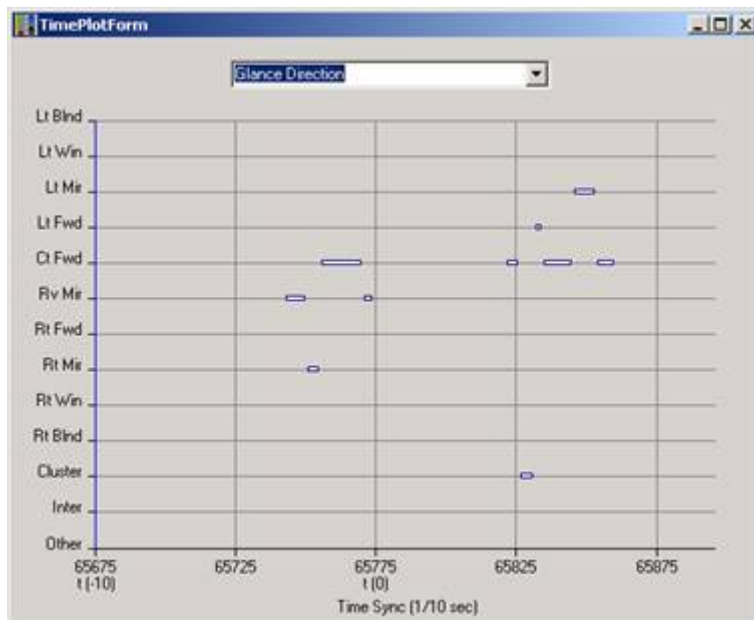


1. Select "Display Event" from the Event menu on the Lane Change menu bar.
2. Select an event to view, such as "e0016s05" (event #16, subject 5) from the Data directory (within the LaneData directory).

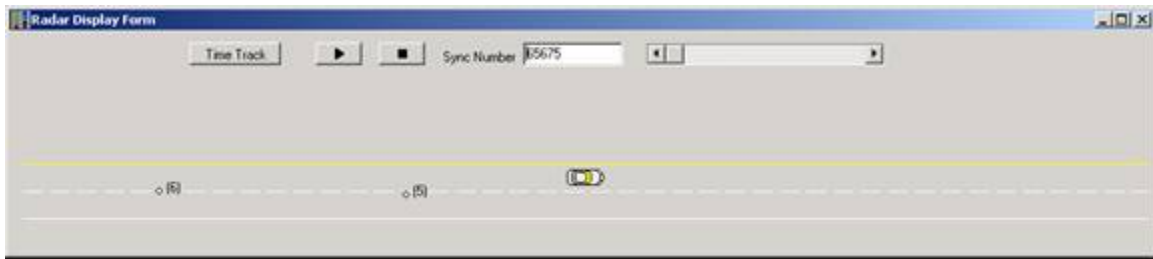


3. Click on Open. The Event Data Form will open:

4. Click on the "Time Plot" button in the Event Data Form window to see the TimePlotForm (time graph):



5. And the Radar Display Form (bird's eye view of the subject vehicle and surrounding radar targets):



6. The TimePlotForm has a pull-down menu to see various parameters:
- Glance Direction
 - Subject Vehicle Speed (mph)
 - Steering Wheel Angle (rad)
 - Lateral Acceleration (g's)
 - Accelerator Position
 - Brake Position
 - Turn Signals
 - Absolute Target Speed (mph)
 - Relative Target Speed (ft/s)
 - Target Distance (ft)
 - Target Angle (degrees)

Note: When either the Target Distance or Target Angle item is selected, a Target Information window will appear. This window provides descriptive information including TTC, time to Proximity Zone about the identified target. Information for each target is available by changing the Target # in the pull-down menu at the top of this window.



7. Select a pull-down menu item as desired.
 - To see multiple items at once, click on the Time Plot button again and a new TimePlotForm (graph) will pop up on top of the previous.
 - Reposition the new graph as desired.
8. The Radar Display Form has simple play and stop buttons and a scroll bar for controlling the movement of the event over time. Notice the synch numbers corresponding to time (1 synch = 1/10 second)
9. The time track button can be toggled to see the radar tracks for a particular target.

Description of Lane Change Program Forms

The Event Data Form includes relevant data for the event as shown below:

The screenshot shows the 'Event Data Form' window with the following fields and values:

Raw Data File:	\\veyglance5\LaneData\RawData\Data_Su	Browse:
Video Tape ID:	S0503 Sed 460 Male SedDrv 102800	
Motivation:	Slow lead vehicle	
Severity:	5 - POV in Proximity Zone	
Urgency:	2 - Urgent, TTC <= 5.5s	
Notes:	Passes on right to pass slow lead, accelerates, and cuts back close to POV behind; urgent because of return maneuver and speed differential. Return initiation = 65852; Conversing with passenger (son?)	
Subject Number:	5	Event Number: 16
Run Number:	7	Sync 10 sec prior: 65675
Age:	35	Begin Sync Number: 65775
Gender:	Male	End Sync Number: 65896
Vehicle:	Sedan	Sync Duration: 121
Usual Vehicle:	Sedan	Lane Data: Finished
Road Type:	460	Lane Curve: Finished
Date:	10-30-2000	Glance Data: Finished
Clock Time:	17:25:36	Target Data: Finished
<input type="button" value="Time Plot"/> <input type="button" value="Show Radar"/> <input type="button" value="Close"/>		

The event Start Sync is the Begin Sync Number, on the middle right side of the form.

The Video Tape Number* is entered into the "Video Tape ID" field in the Event Data Form of the Lane Change program

* See the Video Tape Labeling Convention section at the end of this document.

Notes are entered into the “Notes” field in the LaneChange program.

- Start Synch reflects the first sign of lateral movement (beginning of lane change).
- End Synch reflects the “settling point” of movement (end of lane change).

The following pull down menu items were also selected during analysis:

- Motivation (lane change type) as follows:

Motivation	Description
Slow lead veh	Lane change to pass a vehicle moving slower than the Subject Vehicle’s (SV) preferred speed.
Return	Lane change to return to preferred driving lane.
Enter	Lane change to enter road (e.g., from on-ramp).
Exit/prep exit	Lane change associated with exiting.
Tailgated	Vehicle tailgating/approaching quickly.
Merging veh	Vehicle entering roadway causing SV to change lanes.
Rough/obst avoid	Maneuver to avoid obstacle or rough road surface.
Shoulder	Moving off paved surface/out of travel lanes for any reason.
Lane drop	End of driver’s lane (e.g., road goes from 3 to 2 lanes).
Added lane	Addition of a lane (e.g., road goes from 2 to 3 lanes).
Unintended	Unintended lane deviation (e.g., distraction in car).
Other	Lane change for any other reason or for no discernible reason.

- Severity: A lane change conflict, by definition, requires that there be a vehicle present in the lane into which the driver of the SV wishes to move.

Rating	Description
7	Crash of any sort.
6	Emergency action/unplanned sudden maneuver required to avoid a collision with a vehicle (or object) in the adjacent lane into which the driver of the SV was attempting to move.

Ratings 5 through 1 are assessed at initiation (Start Synch) of the attempted lane change.

5	POV in the proximity zone.
4	POV in the fast approach zone with time to reach closest end of zone, $T_r^\dagger \leq 1.0$ sec.
3	POV in the fast approach zone with time to reach closest end of zone in the range $1.0 < T_r \leq 3.0$ sec.
2	POV in the fast approach zone with time to reach closest end of zone in the range $3.0 < T_r \leq 5.0$ sec.
1	POV in the fast approach zone with time to reach closest end of zone, $T_r > 5.0$ sec, including case where there is no vehicle in the adjacent lane.

[†] T_r is the time required for a Principal Other Vehicle (POV) to reach the front end of the fast approach zone. (This point is 30 ft behind the SV.)

- Urgency: Each type classification can be placed in one of the following categories, according to the urgency of the SV's relationship to vehicle(s) in same lane or opposite adjacent lane (the lane opposite the one into which the SV intends to move):

Rating	Description
4	<u>Critical incident/crash</u> : Physical contact/collision occurs with a vehicle (or object) in the same lane as the SV or the opposite adjacent lane; or a sudden maneuver (braking or swerving) is required to avoid such a collision.
3	<u>Forced</u> : The lane change has a high degree of urgency due to fast closing rate* ($TTC \leq 3s$) and/or close headway/tailway/distance to vehicle in the same or opposite adjacent lane.
2	<u>Urgent</u> : The lane change is somewhat urgent due to moderate closing rate ($5.5s \geq TTC > 3s$) and/or moderate headway/tailway/distance to vehicle in the same or opposite adjacent lane.
1	<u>Non-urgent</u> : The lane change is not urgent, because of a zero or negative closing rate ($TTC > 5.5 s$) with vehicle in the same or opposite adjacent lane, and/or long headway/tailway/distance, and/or lack of vehicles in the same or opposite adjacent lane.

Lane Data includes synch numbers associated with event beginning, inside crossing of the lane line, outside crossing of the lane line and end of the event.

Lane Curve is data that was entered based on a visual estimation of the road curvature based on the video.

* Closing rate between vehicles is the number of seconds (time) it would take for vehicles to collide if the rear vehicle did not maneuver. In other words, it is the time from the initiation (Start Synch) of the lane change to the time when the front bumper of the SV is parallel with the rear bumper of the POV (e.g., when the POV is in front of the SV).

Appendix G: SAS Code and Associated Output for Large Data Set.

One-Way Chi Square SAS Code

```
proc freq data=SASUSER.ALLSLOW ;
  exact chisq;
  tables Gender VehType DrivrTyp Route / nopercnt ;
run;
```

Results for the one way chi square: *Gender*, $X^2(1) = 9.0614$, $p = 0.0028$, *usual vehicle* $X^2(1) = 99.6247$, $p < 0.0001$, and *route* $X^2(1) = 9.0614$, $p = 0.0028$ were significant.

Table G.1: Frequency Chi-Square Values and Probabilities for Route, Usual Vehicle, Gender, and Experimental Vehicle for All Slow Lead Vehicle Lane Changes (N = 3,227).

Main Effect	Pearson chi-square value	df	Probability
Route	9.0614	1	0.0028
Usual Vehicle	99.6247	1	< 0.0001
Gender	9.0614	1	0.0028
Experimental Vehicle	1.0787	1	0.3073

Gray and Bold Italics = significant main effect of $p \leq 0.001$. Gray = significant main effect of $p \leq 0.05$.

Two-way chi square SAS Code:

```
proc freq data=SASUSER.ALLSLOW ;
  exact chisq;
  tables Gender*VehType Gender*DrivrTyp DrivrTyp*Route Gender*Route VehType*Route
  VehType*DrivrTyp/ nopercnt ;
run;
```

Results for the two-way chi square: For Frequency, gender by experimental vehicle, $X^2(1) = 4.7896, p = 0.0286$, and gender by route, $X^2(1) = 158.8966, p < 0.0001$, were significant.

Table G.2: Usual Vehicle by Route Frequency.

Usual Vehicle	Route		Total
	Interstate	Highway	
SUVDrv	705	625	1330
SedDrv	994	903	1897
TOTAL	1699	1528	3227

$$X^2(1) = 0.1163, p = 0.7331$$

Table G.3: Gender by Route Frequency.

Gender	Route		Total
	Interstate	Highway	
Female	983	545	1528
Male	716	983	1699
TOTAL	1699	1528	3227

$$X^2(1) = 158.8966, p < .0001$$

Table G.4: Gender by Usual Vehicle Frequency.

Gender	Usual Vehicle		Total
	SUVDrv	SedDrv	
Female	615	913	1528
Male	715	984	1699
TOTAL	1330	1897	3227

$$X^2(1) = 1.1179, p = 0.2904$$

Table G.5: Gender by Experimental Vehicle Frequency.

Gender	VehType		Total
	SUV	Sed	
Female	719	509	1528
Male	865	824	1699
TOTAL	1584	1643	3227

$$\chi^2(1) = 4.7896, p = 0.0286$$

Table G.6: Experimental Vehicle by Route Frequency.

Experimental Vehicle	Route		Total
	Interstate	Highway	
SUV	845	739	1584
Sed	854	789	1643
TOTAL	1699	1528	3227

$$\chi^2(1) = 0.6053, p = 0.4366$$

Table G.7: Experimental Vehicle by Usual Vehicle Frequency.

Experimental Vehicle	Usual Vehicle		Total
	SUVDrv	SedDrv	
SUV	659	925	1584
Sed	671	972	1643
TOTAL	1330	1897	3227

$$\chi^2(1) = 0.1941, p = 0.6695$$

Table G.8: Two-Way Frequency Chi-Square Values and Probabilities for All Slow Lead Vehicle Lane Changes (N = 3,227).

Interaction	Pearson chi-square value	Df	Probability
Usual Vehicle * Route	0.1163	1	0.7331
Gender * Route	158.8966	1	<0.0001
Gender * Usual Vehicle	1.1179	1	0.2904
Gender * Experimental Vehicle	4.7896	1	0.0286
Experimental Vehicle * Route	0.6053	1	0.4366
Experimental Vehicle * Usual Vehicle	0.1941	1	0.6595

Gray = significant main effect of $p \leq 0.05$

ANOVA SAS Code (N = 2,168) for Duration:

```
proc glm data=SASUSER.ALLSLOW;
class gender vehtype drivrtyp route subj;
where Succ_Mag = "S";
model Dur = gender|vehtype|drivrtyp|route  subj(drivrtyp*gender*route)
vehtype*subj(drivrtyp*gender*route)/ SS3 ;
random subj(drivrtyp*gender*route) ;
Test H = route|drivrtyp|gender E = subj(drivrtyp*gender*route);
Test H = vehtype vehtype*gender vehtype*drivrtyp vehtype*route
gender*vehtype*drivrtyp gender*vehtype*route vehtype*drivrtyp*route
gender*vehtype*drivrtyp*route E = vehtype*subj(drivrtyp*gender*route);
run;
```

Results for the GLM Procedure: There were no significant main effects, two-way, three-way, or four-way interactions.

ANOVA SAS Code (N = 3,227) for Urgency and Severity:

```
proc glm data=SASUSER.ALLSLOW;
class gender vehtype drivrtyp route subj;
model Urg Sev = gender|vehtype|drivrtyp|route  subj(drivrtyp*gender*route)
vehtype*subj(drivrtyp*gender*route)/ SS3 ;
random subj(drivrtyp*gender*route) ;
Test H = route|drivrtyp|gender E = subj(drivrtyp*gender*route);
Test H = vehtype vehtype*gender vehtype*drivrtyp vehtype*route
gender*vehtype*drivrtyp gender*vehtype*route vehtype*drivrtyp*route
gender*vehtype*drivrtyp*route E = vehtype*subj(drivrtyp*gender*route);
run;
```

Results for the GLM Procedure: Route was significant for urgency ($F=5.24$, $p=0.0513$). There were no significant two-way, three-way, or four-way interactions.

Table G.9: ANOVA Summary Table for Duration (N = 2,168).

Source	df	SS	MS	F	Pr > F
<u>Between</u>					
Route	1	17.77	17.77	0.77	0.405
DrivrType	1	30.86	30.86	1.34	0.280
DrivrType*Route	1	3.61	3.61	0.16	0.702
Gender	1	33.15	33.15	1.44	0.264
Gender*Route	1	0.56	0.56	0.02	0.880
Gender*DrivrType	1	7.85	7.85	0.34	0.575
Gender*DrivrType*Route	1	3.78	3.78	0.16	0.696
Subj(Gender*DrivrType*Route)	8	183.71	22.96	4.59	<.0001
<u>Within</u>					
VehType	1	0.37	0.37	0.09	0.775
Gender*VehType	1	1.47	1.47	0.35	0.570
VehType*DrivrType*Route	1	4.19	4.19	1.00	0.346
VehType*Route	1	1.16	1.16	0.28	0.612
Gender*VehType*DrivrType	1	0.04	0.04	0.01	0.928
Gender*VehType*Route	1	0.00	0.00	0.00	0.995
VehType*DrivrType*Route	1	3.72	3.72	0.89	0.373
Gender*VehType*DrivrType*Route	1	1.02	1.02	0.24	0.635
VehType*Sub(Gender*DrivrType*Route)	8	33.45	4.18	0.84	0.571
Model	31	468.65	15.12	3.02	<.0001
Error	2136	10686.61	5.00		
Total	2167	11155.26			

R-Square Coeff Var Root MSE Dur Mean
0.042012 35.73910 2.236760 6.258579

Table G.10: ANOVA Summary Table for Urgency (N = 3,227).

Source	df	SS	MS	F	Pr > F
<u>Between</u>					
Route	1	3.84	3.84	5.24	0.051
DrivrType	1	1.43	1.43	1.96	0.199
DrivrType*Route	1	1.30	1.30	1.77	0.220
Gender	1	1.97	1.97	2.69	0.140
Gender*Route	1	1.01	1.01	1.38	0.273
Gender*DrivrType	1	0.72	0.72	0.98	0.352
Gender*DrivrType*Route	1	0.66	0.66	0.90	0.370
Subj(Gender*DrivrType*Route)	8	5.86	0.73	8.49	<.0001
<u>Within</u>					
VehType	1	0.03	0.03	0.30	0.601
Gender*VehType	1	0.25	0.25	2.80	0.133
VehType*DrivrType*Route	1	0.08	0.08	0.93	0.364
VehType*Route	1	0.00	0.00	0.01	0.939
Gender*VehType*DrivrType	1	0.08	0.08	0.87	0.379
Gender*VehType*Route	1	0.12	0.12	1.35	0.279
VehType*DrivrType*Route	1	0.10	0.10	1.15	0.315
Gender*VehType*DrivrType*Route	1	0.25	0.25	2.82	0.131
VehType*Sub(Gender*DrivrType*Route)	8	0.71	0.09	1.03	0.412
Model	31	21.90	0.71	8.19	<.0001
Error	3195	275.76	0.09		
Total	3226	297.67			

R-Square Coeff Var Root MSE Urg Mean
0.073574 26.90278 0.293788 1.092036

Table G.11: ANOVA Summary Table for Severity (N = 3,227).

Source	df	SS	MS	F	Pr > F
<u>Between</u>					
Route	1	29.90	29.90	3.49	0.099
DrivrType	1	4.70	4.70	0.55	0.480
DrivrType*Route	1	1.55	1.55	0.18	0.682
Gender	1	14.10	14.10	1.65	0.235
Gender*Route	1	0.30	0.30	0.04	0.856
Gender*DrivrType	1	0.09	0.09	0.01	0.920
Gender*DrivrType*Route	1	7.78	7.78	0.91	0.369
Subj(Gender*DrivrType*Route)	8	68.50	8.56	10.82	<.0001
<u>Within</u>					
VehType	1	0.61	0.61	0.16	0.703
Gender*VehType	1	2.32	2.32	0.59	0.463
VehType*DrivrType*Route	1	1.11	1.11	0.29	0.608
VehType*Route	1	0.16	0.16	0.04	0.846
Gender*VehType*DrivrType	1	0.02	0.02	0.01	0.942
Gender*VehType*Route	1	0.75	0.75	0.19	0.673
VehType*DrivrType*Route	1	1.11	1.11	0.29	0.608
Gender*VehType*DrivrType*Route	1	0.01	0.01	0.00	0.956
VehType*Sub(Gender*DrivrType*Route)	8	31.18	3.90	4.92	<.0001
Model	31	180.56	5.82	7.36	<.0001
Error	3195	2528.66	0.79		
Total	3226	2709.22			

R-Square Coeff Var Root MSE Sev Mean
0.066647 71.86079 0.889631 1.237992

Table G.12: Two-Way Distributions of Mean Duration for Route, Usual Vehicle, Gender, and Experimental Vehicle for All Slow Lead Vehicle Lane Changes.

Mean Duration		Usual Vehicle		Gender		Experimental Vehicle	
		SUV Driver	Sedan Driver	Male	Female	SUV	Sedan
Route	Interstate	10.04	10.80	9.56	11.16	10.55	10.42
	Highway	15.29	16.18	14.80	17.48	16.51	15.05
Usual Vehicle	SUV Drv			12.90	12.54	13.03	12.41
	Sedan Drv			12.36	14.20	13.57	12.83
Gender	Male					12.40	12.78
	Female					14.44	12.50

No significant interactions.

Table G.13: Two-Way Distributions of Mean Urgency for Route, Usual Vehicle, Gender, and Experimental Vehicle for All Slow Lead Vehicle Lane Changes.

Mean Urgency		Usual Vehicle		Gender		Experimental Vehicle	
		SUV Driver	Sedan Driver	Male	Female	SUV	Sedan
Route	Interstate	1.05	1.05	1.06	1.04	1.05	1.05
	Highway	1.08	1.20	1.17	1.08	1.15	1.13
Usual Vehicle	SUV Drv			1.08	1.05	1.07	1.06
	Sedan Drv			1.15	1.07	1.12	1.11
Gender	Male					1.13	1.12
	Female					1.05	1.06

No significant interactions.

Table G.14: Two-Way Distributions of Mean Severity for Route, Usual Vehicle, Gender, and Experimental Vehicle for All Slow Lead Vehicle Lane Changes.

Mean Severity		Usual Vehicle		Gender		Experimental Vehicle	
		SUV Driver	Sedan Driver	Male	Female	SUV	Sedan
Route	Interstate	1.25	1.39	1.41	1.28	1.34	1.33
	Highway	1.08	1.19	1.19	1.04	1.14	1.13
Usual Vehicle	SUV Drv			1.23	1.10	1.16	1.17
	Sedan Drv			1.31	1.28	1.32	1.28
Gender	Male					1.30	1.25
	Female					1.18	1.21

No significant interactions.

Appendix H: SAS Code and Associated Output for Sample Data Set.

FULL ANALYSIS of SAMPLE (N=120)

Duration

```
proc glm data= SASUSER.SAMPLE_120;
class gender vehtype drivrtyp route subj;
model dur = gender|vehtype|drivrtyp|route  subj(drivrtyp*gender*route)
vehtype*subj(drivrtyp*gender*route)/ SS3 ;
random subj(drivrtyp*gender*route) ;
Test H = route|drivrtyp|gender E = subj(drivrtyp*gender*route);
Test H = vehtype vehtype*gender vehtype*drivrtyp vehtype*route
gender*vehtype*drivrtyp gender*vehtype*route vehtype*drivrtyp*route
gender*vehtype*drivrtyp*route E = vehtype*subj(drivrtyp*gender*route);
run;
end;
```

Urgency and Severity

```
proc glm data= SASUSER.SAMPLE_092703_3;
class gender vehtype drivrtyp route subj;
model Urg Sev = gender|vehtype|drivrtyp|route  subj(drivrtyp*gender*route)
vehtype*subj(drivrtyp*gender*route)/ SS3 ;
random subj(drivrtyp*gender*route) ;
Test H = route|drivrtyp|gender E = subj(drivrtyp*gender*route);
Test H = vehtype vehtype*gender vehtype*drivrtyp vehtype*route
gender*vehtype*drivrtyp gender*vehtype*route vehtype*drivrtyp*route
gender*vehtype*drivrtyp*route E = vehtype*subj(drivrtyp*gender*route);
run;
end;
```

Results for the GLM Procedure:

Experimental vehicle was significant for duration ($F=14.61$, $p=0.0051$),

Route was significant for urgency ($F=9.62$, $p=0.0146$),

Usual vehicle was significant for urgency ($F=11.08$, $p=0.0104$),

*The experimental vehicle*usual vehicle*route interaction was significant for urgency ($F=20.78$, $p=0.0019$), and the gender*experimental vehicle*usual vehicle*route interaction was significant for urgency ($F=6.71$, $p=0.0321$). There were no significant effects or interactions for severity.*

Table H.1: ANOVA Summary Table for Duration (N = 120).

Source	df	SS	MS	F	Pr > F
<u>Between</u>					
Route	1	0.44	0.44	0.26	0.627
DrivrType	1	4.21	4.21	2.44	0.157
DrivrType*Route	1	0.63	0.63	0.36	0.563
Gender	1	0.02	0.02	0.01	0.921
Gender*Route	1	0.35	0.35	0.20	0.665
Gender*DrivrType	1	2.15	2.15	1.25	0.296
Gender*DrivrType*Route	1	0.00	0.00	0.00	0.981
Subj(Gender*DrivrType*Route)	8	13.78	1.72	1.46	
<u>Within</u>					
VehType	1	1.93	1.93	1.77	0.225
Gender*VehType	1	0.90	0.90	0.83	0.393
VehType*DrivrType*Route	1	0.42	0.42	0.39	0.553
VehType*Route	1	1.72	1.72	1.58	0.249
Gender*VehType*DrivrType	1	4.25	4.25	3.91	0.089
Gender*VehType*Route	1	2.27	2.27	2.09	0.191
VehType*DrivrType*Route	1	2.42	2.42	2.23	0.179
Gender*VehType*DrivrType*Route	1	2.03	2.03	1.87	0.213
VehType*Sub(Gender*DrivrType*Route)	7	7.60	1.09	0.92	
Model	30	40.33	1.34	1.14	0.329
Error	62	73.36	1.18		
Total	92	113.69			

R-Square Coeff Var Root MSE Dur Mean
0.354703 19.32477 1.087798 5.629032

Table H.2: ANOVA Summary Table for Urgency (N = 120).

Source	df	SS	MS	F	Pr > F
<u>Between</u>					
Route	1	2.87	2.87	9.62	0.015
DrivrType	1	3.31	3.31	11.08	0.010
DrivrType*Route	1	1.36	1.36	4.57	0.065
Gender	1	0.12	0.12	0.41	0.538
Gender*Route	1	0.06	0.06	0.21	0.660
Gender*DrivrType	1	0.00	0.00	0.00	0.987
Gender*DrivrType*Route	1	0.05	0.05	0.16	0.695
Subj(Gender*DrivrType*Route)	8	2.39	0.30	0.69	0.700
<u>Within</u>					
VehType	1	0.00	0.00	0.03	0.878
Gender*VehType	1	0.25	0.25	2.07	0.188
VehType*DrivrType*Route	1	0.17	0.17	1.42	0.267
VehType*Route	1	0.01	0.01	0.12	0.739
Gender*VehType*DrivrType	1	0.28	0.28	2.31	0.167
Gender*VehType*Route	1	0.43	0.43	3.51	0.098
VehType*DrivrType*Route	1	2.53	2.53	20.78	0.002
Gender*VehType*DrivrType*Route	1	0.82	0.82	6.71	0.032
VehType*Sub(Gender*DrivrType*Route)	8	0.97	0.12	0.28	
Model	31	17.84	0.58	1.33	0.153
Error	88	38.13	0.43		
Total	119	55.97			

R-Square Coeff Var Root MSE Urg Mean
0.318727 43.40041 0.658239 1.516667

Table H.3: ANOVA Summary Table for Severity (N = 120).

Source	df	SS	MS	F	Pr > F
<u>Between</u>					
Route	1	13.01	13.01	3.84	0.086
DrivrType	1	0.38	0.38	0.11	0.746
DrivrType*Route	1	0.05	0.05	0.01	0.911
Gender	1	12.14	12.14	3.58	0.095
Gender*Route	1	3.81	3.81	1.12	0.320
Gender*DrivrType	1	3.28	3.28	0.97	0.354
Gender*DrivrType*Route	1	1.28	1.28	0.38	0.557
Subj(Gender*DrivrType*Route)	8	27.13	3.39	1.45	0.188
<u>Within</u>					
VehType	1	2.11	2.11	0.34	0.575
Gender*VehType	1	1.36	1.36	0.22	0.652
VehType*DrivrType*Route	1	2.52	2.52	0.41	0.541
VehType*Route	1	1.09	1.09	0.18	0.686
Gender*VehType*DrivrType	1	4.96	4.96	0.80	0.397
Gender*VehType*Route	1	8.98	8.98	1.45	0.263
VehType*DrivrType*Route	1	0.23	0.23	0.04	0.852
Gender*VehType*DrivrType*Route	1	16.03	16.03	2.59	0.146
VehType*Sub(Gender*DrivrType*Route)	8	49.52	6.19	2.65	0.012
Model	31	145.56	4.70	2.01	0.006
Error	88	205.91	2.34		
Total	119	351.47			

R-Square Coeff Var Root MSE Sev Mean
0.414142 55.96342 1.529667 2.733333

Table H.4: Two-Way Distributions of Frequency for Route, Usual Vehicle, Gender, and Experimental Vehicle for Slow Lead Vehicle Lane Change Sample.

Frequency		Usual Vehicle		Gender		Experimental Vehicle	
		SUV Driver	Sedan Driver	Male	Female	SUV	Sedan
Route	Interstate	29	36	35	30	34	31
	Highway	19	36	39	16	27	28
Usual Vehicle	SUV Drv			29	19	23	38
	Sedan Drv			45	27	25	34
Gender	Male					42	32
	Female					19	27

No Significant Interactions

Table H.5: Two-Way Distributions of Mean Duration for Route, Usual Vehicle, Gender, and Experimental Vehicle for Slow Lead Vehicle Lane Change Sample.

Mean Duration		Usual Vehicle		Gender		Experimental Vehicle	
		SUV Driver	Sedan Driver	Male	Female	SUV	Sedan
Route	Interstate	6.14	5.44	5.64	5.88	5.64	5.87
	Highway	5.23	5.14	5.34	5.47	5.13	5.61
Usual Vehicle	SUV Drv			5.89	6.21	5.97	6.31
	Sedan Drv			5.22	5.40	9.88	12.64
Gender	Male					5.23	5.80
	Female					5.81	5.69

No Significant Interactions

Table H.6: Two-Way Distributions of Mean Urgency for Route, Usual Vehicle, Gender, and Experimental Vehicle for Slow Lead Vehicle Lane Change Sample.

Mean Urgency		Usual Vehicle		Gender		Experimental Vehicle	
		SUV Driver	Sedan Driver	Male	Female	SUV	Sedan
Route	Interstate	1.28	1.36	1.34	1.30	1.29	1.35
	Highway	1.37	1.94	1.85	1.50	1.74	1.75
Usual Vehicle	SUV Drv			1.34	1.26	1.26	1.63
	Sedan Drv			1.78	1.44	1.36	1.68
Gender	Male					1.57	1.66
	Female					1.32	1.41

No Significant Interactions

Table H.7: Two-Way Distributions of Mean Severity for Route, Usual Vehicle, Gender, and Experimental Vehicle for Slow Lead Vehicle Lane Change Sample.

Mean Severity		Usual Vehicle		Gender		Experimental Vehicle	
		SUV Driver	Sedan Driver	Male	Female	SUV	Sedan
Route	Interstate	3.03	2.89	3.03	2.87	3.00	2.90
	Highway	2.26	2.58	2.82	1.63	2.44	2.50
Usual Vehicle	SUV Drv			2.90	2.47	2.61	2.84
	Sedan Drv			2.93	2.41	2.84	2.62
Gender	Male					3.00	2.81
	Female					2.21	2.59

No significant interactions.

ONE WAY CHI SQUARES for Sample (N = 120)

SAS code for one-way chi-squares for each dependent measure, in terms of frequency.

```
proc freq data=SASUSER.SAMPLE ;  
    exact chisq;  
    tables Gender VehType DrivrTyp Route / nopercnt ;  
run;
```

Results for the one way Chi Square: Gender, $X^2(1) = 6.5333$, $p = 0.0106$, and usual vehicle, $X^2(1) = 4.80$, $p < 0.0285$, was significant.

Table H.8: Gender One Way Chi Square Results.

Gender	Frequency
Female	46
Male	74
Chi-Square	6.5333
DF	1
Pr > ChiSq	< 0.0106

Table H.9: Experimental Vehicle One Way Chi Square Results.

Experimental Vehicle	Frequency
SUV	61
Sed	59
Chi-Square	0.0333
DF	1
Pr > ChiSq	0.8551

Table H.10: Usual Vehicle One Way Chi Square Results.

Usual Vehicle	Frequency
SUV Driver	48
Sedan Driver	72
Chi-Square	4.8000
DF	1
Pr > ChiSq	0.0285

Table H.11: Route One Way Chi Square Results.

Experimental Vehicle	Frequency
SUV	65
Sed	55
Chi-Square	0.8333
DF	1
Pr > ChiSq	0.3613

TWO WAY CHI SQUARES for Sample (N = 120)

SAS code for all possible two-way combinations for each dependent measure, in terms of frequency.

```
proc freq data=SASUSER.SAMPLE ;
  exact chisq;
  tables Gender*VehType Gender*DrivrTyp DrivrTyp*Route Gender*Route
  VehType*Route VehType*DrivrTyp/ nopercnt ;
run;
```

Results for the two-way chi square: *For Frequency, no interactions were significant; however the gender by route interaction had a $X^2(1) = 3.6692, p = 0.0554$.*

Table H.12: Gender by Experimental Vehicle Frequency.

Gender	Experimental Vehicle		Total
	SUV	Sed	
Female	19	27	46
Male	42	32	74
TOTAL	61	59	120

$$X^2(1) = 2.7101, p = 0.0997$$

Table H.13: Gender by Usual Vehicle Frequency.

Gender	Usual Vehicle		Total
	SUVDrv	SedDrv	
Female	19	27	46
Male	29	45	74
TOTAL	48	72	120

$$X^2(1) = 0.0529, p = 0.8181$$

Table H.14: Usual Vehicle by Route Frequency.

Usual Vehicle	Route		Total
	Interstate	Highway	
SUVDrv	29	19	48
SedDrv	36	36	72
TOTAL	65	55	120

$$\chi^2(1) = 1.2587, p = 0.2619$$

Table H.15: Gender by Route Frequency.

Gender	Route		Total
	Interstate	Highway	
Female	30	16	46
Male	35	30	74
TOTAL	65	55	120

$$\chi^2(1) = 3.6691, p = 0.0554$$

Table H.16: Experimental Vehicle by Route Frequency.

Experimental Vehicle	Route		Total
	Interstate	Highway	
SUV	34	27	61
Sed	31	28	59
TOTAL	65	55	120

$$\chi^2(1) = 0.1233, p = 0.7254$$

Table H.17: Experimental Vehicle by Usual Vehicle Frequency.

Experimental Vehicle	Usual Vehicle		Total
	SUVDrv	SedDrv	
SUV	23	38	61
Sed	25	34	59
TOTAL	48	72	120

$$\chi^2(1) = 0.2723, p = 0.6018$$

Table H.18: Two-Way Distributions of Frequency for Route, Usual Vehicle, Gender, and Experimental Vehicle for Slow Lead Vehicle Lane Change Sample.

Frequency		Usual Vehicle		Gender		Experimental Vehicle	
		SUV Driver	Sedan Driver	Male	Female	SUV	Sedan
Route	Interstate	29	36	35	30	34	31
	Highway	19	36	19	16	27	28
Usual Vehicle	SUV Drv			29	19	23	38
	Sedan Drv			45	27	25	34
Gender	Male					42	32
	Female					19	27

No Significant Interactions

Table H.19: Two-Way Frequency Chi-Square Values and Probabilities for Slow Lead Vehicle Lane Change Sample (N = 120).

Interaction	Pearson chi-square value	df	Probability
Usual Vehicle * Route	1.2587	1	0.2619
Gender * Experimental Vehicle	2.7101	1	0.0997
Gender * Usual Vehicle	0.0529	1	0.8181
Experimental Vehicle * Usual Vehicle	0.2723	1	0.6018
Gender * Route	3.6692	1	0.0554
Experimental Vehicle * Route	0.1233	1	0.7254

No Significant Interactions

Appendix I: Logistic Regression SAS Code.

Sample Data (N = 120) vs. Baseline (N = 40)

Vehicle Model

```

proc logistic descending nosimple data=SASUSER.Sev_all_x_smaller;
model type= vehspeed steer accel brake
TTC_1 TTC_2 AdjDist1 AdjDist2
/ selection = forward
slentry=.05
slstay=.05
details
ctable;
output out=pred p=phat lower=lcl upper=ucl;
run;
proc print data=pred;
run;

```

Relevant Output:

Table I.1: Analysis of Maximum Likelihood Estimates (Vehicle Model).

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	8.930	1.564	32.614	<.0001
TTC_1	1	-0.118	0.021	31.018	<.0001
AdjDist1	1	-0.014	0.004	14.226	0.0002
AdjDist2	1	-0.008	0.003	7.466	0.0063

Table I.2: Odds Ratio Estimates (Vehicle Model).

Effect	Point Estimate	95% Wald Confidence Limits	
TTC_1	0.889	0.853	0.926
AdjDist1	0.986	0.979	0.993
AdjDist2	0.992	0.986	0.998

Table I.3: Summary of Forward Selection (Vehicle Model).

Forward Selection				
Step	Effects Entered	DF	Chi-Square	Pr > ChiSq
1	TTC_1	1	78.02	<.0001
2	AdjDist1	1	26.65	<.0001
3	AdjDist2	1	8.72	0.0031
Analysis of Effects Not in the Model				
	Effect Not Entered	DF	Chi-Square	Pr > ChiSq
	VehSpeed	1	1.04	0.308
	Steer	1	1.06	0.304
	Accel	1	0.09	0.765
	Brake	1	0.17	0.682
	TTC_2	1	0.05	0.828

Vehicle + Glance Model

```

proc logistic descending nosimple data=SASUSER.Sev_all_x_smaller;
model type= vehspeed steer accel brake RVM LBS LM LW RM InstrCls
TTC_1 TTC_2 AdjDist1 AdjDist2
/ selection = forward
slentry=.05
slstay=.05
details
ctable;
output out=pred p=phat lower=lcl upper=ucl;
run;
proc print data=pred;
run;

```

Relevant Output:

Table I.4: Analysis of Maximum Likelihood Estimates (Vehicle + Glance Model).

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	12.616	3.502	12.977	0.0003
LM	1	5.922	1.901	9.703	0.0018
LW	1	5.502	2.010	7.493	0.0062
TTC_1	1	-0.214	0.059	13.274	0.0003
AdjDist1	1	-0.028	0.009	9.229	0.0024
AdjDist2	1	-0.010	0.004	4.865	0.0274

Table I.5: Odds Ratio Estimates (Vehicle + Glance Model).

Effect	Point Estimate	95% Wald Confidence Limits	
LM	373.167	8.987	>999.999
LW	245.226	4.771	>999.999
TTC_1	0.807	0.719	0.906
AdjDist1	0.972	0.955	0.990

Table I.6: Summary of Forward Selection (Vehicle + Glance Model).

Forward Selection				
Step	Effects Entered	DF	Chi-Square	Pr > ChiSq
1	TTC_1	1	78.02	<.0001
2	AdjDist1	1	26.65	<.0001
3	LM	1	16.16	<.0001
4	LW	1	11.61	0.001
5	AdjDist2	1	5.99	0.014
Analysis of Effects Not in the Model				
	Effect Not Entered	DF	Chi-Square	Pr > ChiSq
	VehSpeed	1	0.20	0.655
	Steer	1	0.51	0.476
	Accel	1	0.00	0.980
	Brake	1	0.07	0.799
	RVM	1	1.84	0.175
	LBS	1	1.26	0.262
	RM	1	0.04	0.848
	InstrCls	1	0.15	0.701
	TTC_2	1	0.04	0.847

Vehicle + Signal (binary) Model

```

proc logistic descending nosimple data=SASUSER.Sev_all_x_smaller;
model type= vehspeed steer accel brake sig_on
TTC_1 TTC_2 AdjDist1 AdjDist2
/ selection = forward
slentry=.05
slstay=.05
details
ctable;
output out=pred p=phat lower=lcl upper=ucl;
run;
proc print data=pred;
run;

```

Relevant Output:

Table I.7: Analysis of Maximum Likelihood Estimates (Vehicle + Signal [binary] Model).

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	10.058	3.014	11.137	0.001
Brake	1	4.105	2.213	3.441	0.064
sig_on	1	18.592	196.500	0.009	0.925
TTC_1	1	-0.221	0.069	10.308	0.001
AdjDist1	1	-0.013	0.006	4.731	0.030
AdjDist2	1	-0.010	0.005	4.741	0.029

Table I.8: Odds Ratio Estimates (Vehicle + Signal [binary] Model).

Effect	Point Estimate	95% Wald Confidence Limits	
Brake	60.616	0.793	>999.999
sig_on	>999.999	<0.001	>999.999
TTC_1	0.802	0.701	0.918
AdjDist1	0.987	0.975	0.999
AdjDist2	0.990	0.981	0.999

Table I.9: Summary of Forward Selection (Vehicle + Signal [binary] Model).

Forward Selection				
Step	Effects Entered	DF	Chi-Square	Pr > ChiSq
1	TTC_1	1	78.025	<.0001
2	sig_on	1	44.628	<.0001
3	AdjDist2	1	8.001	0.0047
4	AdjDist1	1	4.171	0.0411
5	Brake	1	5.233	0.0222
Analysis of Effects Not in the Model				
	Effect Not Entered	DF	Chi-Square	Pr > ChiSq
	VehSpeed	1	1.56	0.212
	Steer	1	0.16	0.690
	Accel	1	0.36	0.548
	TTC_2	1	1.40	0.237

Vehicle + Signal (timing) Model

```

proc logistic descending nosimple data=SASUSER.Sev_all_x_smaller;
model type= vehspeed steer accel brake sig_timing
TTC_1 TTC_2 AdjDist1 AdjDist2
/ selection = forward
slentry=.05
slstay=.05
details
ctable;
output out=pred p=phat lower=lcl upper=ucl;
run;
proc print data=pred;
run;

```

Relevant Output:

Table I.10: Analysis of Maximum Likelihood Estimates (Vehicle + Signal [timing] Model).

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	10.057	3.013	11.141	0.001
Brake	1	4.102	2.212	3.440	0.064
sig_timing	1	41.381	65.928	0.394	0.530
TTC_1	1	-0.221	0.069	10.313	0.001
AdjDist1	1	-0.013	0.006	4.730	0.030
AdjDist2	1	-0.010	0.005	4.744	0.029

Table I.11: Odds Ratio Estimates (Vehicle + Signal [timing] Model).

Effect	Point Estimate	95% Wald Confidence Limits	
Brake	60.473	0.792	>999.999
sig_timing	>999.999	<0.001	>999.999
TTC_1	0.802	0.701	0.918
AdjDist1	0.987	0.975	0.999
AdjDist2	0.990	0.981	0.999

Table I.12: Summary of Forward Selection (Vehicle + Signal [timing] Model).

Forward Selection				
Step	Effects Entered	DF	Chi-Square	Pr > ChiSq
1	TTC_1	1	78.025	<.0001
2	sig_timing	1	34.297	<.0001
3	AdjDist2	1	8.020	0.005
4	AdjDist1	1	4.192	0.041
5	Brake	1	5.246	0.022
Analysis of Effects Not in the Model				
	Effect Not Entered	DF	Chi-Square	Pr > ChiSq
	VehSpeed	1	1.58	0.208
	Steer	1	0.18	0.669
	Accel	1	0.39	0.535
	TTC_2	1	1.42	0.233

Vehicle + Glance + Signal (binary) Model

```

proc logistic descending nosimple data=SASUSER.Sev_all_x_smaller;
model type= vehspeed steer accel brake sig_on_att0
TTC_1 TTC_2 AdjDist1 AdjDist2 RVM LBS LM LW RM InstrCls
/ selection = forward
slentry=.05
slstay=.05
details
ctable;
output out=pred p=phat lower=lcl upper=ucl;
run;
proc print data=pred;
run;

```

Table I.13: Analysis of Maximum Likelihood Estimates (Vehicle + Glance + Signal [binary] Model).

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	12.323	3.926	9.852	0.002
sig_on_att0	1	13.282	239.200	0.003	0.956
TTC_1	1	-0.224	0.069	10.635	0.001
AdjDist1	1	-0.025	0.011	5.513	0.019
AdjDist2	1	-0.011	0.005	5.004	0.025
LM	1	5.907	2.489	5.634	0.018
LW	1	5.036	2.297	4.808	0.028

Table I.14: Odds Ratio Estimates (Vehicle + Glance + Signal [binary] Model).

Effect	Point Estimate	95% Wald Confidence Limits	
sig_on_att0	>999.999	<0.001	>999.999
TTC_1	0.799	0.698	0.914
AdjDist1	0.975	0.955	0.996
AdjDist2	0.989	0.979	0.999
LM	367.584	2.799	>999.999
LW	153.775	1.706	>999.999

Table I.15: Summary of Forward Selection (Vehicle + Glance + Signal [binary] Model).

Forward Selection				
Step	Effects Entered	DF	Chi-Square	Pr > ChiSq
1	TTC_1	1	78.025	<.0001
2	AdjDist1	1	26.650	<.0001
3	LM	1	16.159	<.0001
4	LW	1	11.612	0.001
5	AdjDist2	1	5.986	0.014
6	sig_on_att0	1	5.347	0.021
Analysis of Effects Not in the Model				
	Effect Not Entered	DF	Chi-Square	Pr > ChiSq
	VehSpeed	1	0.239	0.625
	Steer	1	3.433	0.064
	Accel	1	0.262	0.609
	Brake	1	0.341	0.559
	TTC_2	1	0.001	0.976
	RVM	1	2.300	0.129
	LBS	1	0.137	0.712
	RM	1	0.003	0.958
	InstrCls	1	2.139	0.144

Vehicle + Glance + Signal (timing) Model

```

proc logistic descending nosimple data=SASUSER.Sev_all_x_smaller;
model type= vehspeed steer accel brake RVM LBS LM LW RM InstrCls
TTC_1 TTC_2 AdjDist1 AdjDist2 sig_timing
/ selection = forward
slentry=.05
slstay=.05
details
ctable;
output out=pred p=phat lower=lcl upper=ucl;
run;
proc print data=pred;
run;

```

Table I.16: Analysis of Maximum Likelihood Estimates (Vehicle + Glance + Signal [timing] Model).

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	24.384	15.55	2.459	0.117
RVM	1	4.931	4.13	1.428	0.232
LM	1	11.579	8.36	1.919	0.166
LW	1	26.945	18.16	2.201	0.138
InstrCls	1	-5.356	3.78	2.006	0.157
TTC_1	1	-0.727	0.49	2.239	0.135
AdjDist1	1	-0.067	0.04	2.520	0.112
sig_timing	1	11.632	7.54	2.378	0.123

Table I.17: Odds Ratio Estimates (Vehicle +Glance + Signal [timing] Model)

Effect	Point Estimate	95% Wald Confidence Limits	
RVM	138.461	0.043	>999.999
LM	>999.999	0.008	>999.999
LW	>999.999	<0.001	>999.999
InstrCls	0.005	<0.001	7.811
TTC_1	0.483	0.186	1.253
AdjDist1	0.935	0.861	1.016
sig_timing	>999.999	0.043	>999.999

Table I.18: Summary of Forward Selection (Vehicle + Glance + Signal [timing] Model).

Forward Selection				
Step	Effects Entered	DF	Chi-Square	Pr > ChiSq
1	TTC 1	1	78.02	<.0001
2	sig_timing	1	34.30	<.0001
3	LW	1	9.11	0.003
4	AdjDist1	1	7.74	0.005
5	LM	1	5.89	0.015
6	RVM	1	4.97	0.026
7	InstrCls	1	4.76	0.029
Analysis of Effects Not in the Model				
	Effect Not Entered	DF	Chi-Square	Pr > ChiSq
	VehSpeed	1	2.53	0.112
	Steer	1	1.91	0.167
	Accel	1	1.78	0.182
	Brake	1	2.86	0.091
	LBS	1	2.93	0.087
	RM	1	1.77	0.183
	TTC 2	1	2.19	0.139
	AdjDist2	1	2.79	0.095

Validation Set (N = 85) vs. Baseline (N = 40)

Models were run in a manner similar to those for the large set. SAS code for only one example is displayed.

Vehicle + Glance + Signal (timing) Model (signal timing) for Validation Set of Data

```
proc logistic descending nosimple data=SASUSER.Second_set;
model type= vehspeed steer accel brake RVM LBS LM LW RM InstrCls
TTC_1 TTC_2 AdjDist1 AdjDist2 sig_on_att0
  / selection = forward
    slentry=.05
    slstay=.05
    details
    ctable;

output out=pred p=phat lower=lcl upper=ucl;
run;
proc print data=pred;
run
```

Appendix J: Descriptive Results of Dependent Variables.

Table J.1: Frequency Counts of Events for Lane Change Sample, Baseline Events, and Totals.

	Type		Gender		VehType		DrivrTyp		Route		Dir		Succ_Mag		
N	160		160		160		160		160		120		120		
Level	Slow	Baseline	M	F	Sedan	SUV	SedDrv	SUVDrv	US460	I81	Left	Right	Single	Pass	Unsuc.
LCs	120	0	74	46	59	61	72	48	55	65	113	7	93	25	2
Base	0	40	21	19	20	20	22	18	19	21	NA	NA	NA	NA	2
Total	120	40	95	65	79	81	94	66	74	86	113	7	93	25	2

Table J.2: Descriptive Statistics for Duration, Ratings, and Vehicle Parameters.

	Dur	Urg	Sev	VehSpeed	Steer	LatAccel
LCs	(seconds)	(1 to 3)	(1 to 5)	(mph)	(rads)	(gs)
Avg	5.58	1.52	2.73	58.79	0.12	0.03
Min	2.90	1.00	1.00	32.31	-0.33	-0.12
Max	12.20	3.00	5.00	76.15	0.49	0.20
SD	1.33	0.69	1.72	9.49	0.20	0.05
N	120	120	120	120	120	120
Baseline						
Avg	10.00	1.00	1.00	64.04	0.13	0.02
Min	10.00	1.00	1.00	43.27	-0.16	-0.07
Max	10.00	1.00	1.00	78.04	0.36	0.12
SD	0.00	0.00	0.00	7.60	0.14	0.04
N	40	40	40	40	40	40
ALL						
Avg	6.68	1.39	2.30	60.10	0.12	0.02
Min	2.90	1.00	1.00	32.31	-0.33	-0.12
Max	12.20	3.00	5.00	78.04	0.49	0.20
SD	2.24	0.63	1.67	9.31	0.19	0.05
N	160	160	160	160	160	160

Table J.3: Turn Signal Statistics.

	sig@t₀	sig_anytime	sig_timing	Transformed Data
LCs	(single pt)	(before/after t₀)	(seconds before/after t₀)	(0 = no signal; >0 = signal)
Avg	0.41	0.64	-0.58	1.66
Min	0.00	0.00	-5.60	0.00
Max	1.00	1.00	1.90	7.60
SD	0.49	0.48	1.21	1.57
N	49	77	77	77
Total	120	120	120	120

Table J.4: Additional Vehicle Data.

	Lead Vehicle					Rear Adjacent Vehicle				
	Dist1	TTC1	Azmuth1	Vel1	RelVel1	Dist2	TTC2	Azmuth2	Vel2	RelVel2
LCs	(feet)	(seconds)	(radians)	(mph)	(mph)	(feet)	(seconds)	(radians)	(mph)	(mph)
Avg	109.35	18.28	0.00	50.69	-10.41	136.63	35.13	0.00	44.97	24.95
Min	23.50	-7.45	-0.11	13.00	-69.10	-20.00	0.01	-0.11	-0.33	-28.60
Max	450.00	60.00	0.11	70.00	30.89	345.90	61.00	0.10	79.70	106.52
SD	74.52	15.04	0.03	12.73	14.55	123.99	18.91	0.04	29.44	44.61
N	120	120	118	120	120	120	120	88	120	120
Baseline										
Avg	235.00	51.32	-0.01	45.34	0.04	219.00	40.80	0.00	43.76	3.65
Min	72.40	17.50	-0.09	-0.16	-12.40	-65.00	-0.75	-0.10	-0.03	-13.00
Max	400.00	61.00	0.06	72.30	104.40	400.00	61.00	0.14	78.50	99.70
SD	95.03	14.12	0.03	28.89	17.32	121.74	20.64	0.06	31.66	21.68
N	40	40	39	40	40	40	40	38	40	40
ALL										
Avg	140.76	26.54	0.00	49.35	-7.80	157.22	36.55	0.00	44.67	19.62
Min	23.50	-7.45	-0.11	-0.16	-69.10	-65.00	-0.75	-0.11	-0.33	-28.60
Max	450.00	61.00	0.11	72.30	104.40	400.00	61.00	0.14	79.70	106.52
SD	96.69	20.60	0.03	18.20	15.90	128.14	19.45	0.05	29.91	41.11
N	160	160	157	160	160	160	160	126	160	160

Table J.5: Eye Glance Data in Terms of Glance Occurrence.

	F	RVM	LM	LW	LBS	IC	RM	OINT	RBS	RW
LCs										
Avg	0.99	0.46	0.50	0.27	0.28	0.18	0.04	0.01	0.02	0.01
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SD	0.09	0.50	0.50	0.44	0.45	0.39	0.20	0.09	0.13	0.09
N	119	55	60	32	34	22	5	1	2	1
Baseline										
Avg	1.00	0.23	0.10	0.08	0.00	0.25	0.05	0.05	0.00	0.00
Min	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	1.00	1.00	1.00	1.00	0.00	1.00	1.00	1.00	0.00	0.00
SD	0.00	0.42	0.30	0.27	0.00	0.44	0.22	0.22	0.00	0.00
N	40	9	4	3	0	10	2	2	0	0
ALL										
Avg	0.99	0.40	0.40	0.22	0.21	0.20	0.04	0.02	0.01	0.01
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SD	0.08	0.49	0.49	0.41	0.41	0.40	0.21	0.14	0.11	0.08
N	159	64	64	35	34	32	7	3	2	1

Table J.6: Frequency Counts of Events for Validation Sample.

	Type		Gender		VehType		DrivrTyp		Route	
N	85		85		85		85		85	
Level	Slow	Baseline	M	F	Sedan	SUV	SedDrv	SUVDrv	US460	I81
Valid	85	0	52	33	37	48	62	23	14	74

Table J.7: Descriptive Statistics for Duration, Ratings, and Vehicle Parameters For Validation Sample.

	Dur	Urg	Sev	VehSpeed	Steer	LatAccel
LCs	(seconds)	(1 to 3)	(1 to 5)	(mph)	(rads)	(gs)
Avg	12.28	1.08	4.40	61.01	0.15	0.02
Min	43.10	2.00	5.00	77.47	0.45	0.16
Max	4.50	1.00	1.00	39.23	-0.24	-0.13
SD	10.34	0.28	1.32	8.68	0.16	0.05
N	85	85	85	85	85	85

Table J.8: Turn Signal Statistics for Validation Sample.

	sig@t₀
LCs	(single pt)
Avg	0.54
Min	1.00
Max	0.00
SD	0.50
N	46
Total	85

Table J.9: Additional Vehicle Data for Validation Sample.

	Lead Vehicle					Rear Adjacent Vehicle				
	Dist1	TTC1	Azmuth1	Vel1	RelVel1	Dist2	TTC2	Azmuth2	Vel2	RelVel2
LCs	(feet)	(seconds)	(radians)	(mph)	(mph)	(feet)	(seconds)	(radians)	(mph)	(mph)
Avg	99.35	25.89	0.00	57.72	-4.83	152.45	26.94	0.00	63.02	-2.16
Min	25.90	4.10	-0.10	27.60	-28.20	32.00	7.5	-0.15	33.70	-21.80
Max	296.10	60.00	0.08	71.60	19.20	398.50	60.0	0.12	78.20	33.30
SD	59.10	17.27	0.03	8.41	8.79	83.41	13.25	0.07	8.98	9.21
N	85	85	85	85	85	85	85	85	85	85

Table J.10: Eye Glance Data in Terms of Glance Occurrence for Validation Data.

	F	RVM	LM	LW	LBS	IC	RM	RBS
Validation								
Avg	1.00	0.62	0.49	0.41	0.26	0.13	0.06	0.01
SD	0.00	0.49	0.50	0.50	0.44	0.34	0.24	0.11
N	85	53	42	35	22	11	5	1

VITA

Erik Charles Buck Olsen was born in Bellefonte, Pennsylvania on September 13, 1968. In 1980, he moved to Santa Clara, California. He received his Bachelor of Arts degree in Interpersonal and Organizational Speech Communication from California State University, Long Beach in June 1990. He earned a Master of Science in Human Factors and Ergonomics from San Jose State in August 1996. During his Master's studies he was an intern at SRI International. While there he assisted in various video data collection efforts involving multimodal interfaces (voice and pen input). His thesis topic, sponsored by an American Automobile Association Foundation for Traffic Safety Grant for Master's Thesis Research, involved an investigation of simulated versus on-road driving and driver evaluation. From 1995 to 1998, he worked as a Research Associate with Monterey Technologies, Inc. where he was involved in various government and military human factors design and evaluation projects.

Since July 1998, during his graduate studies at Virginia Tech, he was a Graduate Research Assistant for the Virginia Tech Transportation Institute and was involved in various efforts including naturalistic driving data collection, driver distraction, effect of fatigue and alcohol on driving, vehicle lighting and visibility, roadway and intersection analysis, local short haul driver behavior, and was involved in supporting the development of a driver error taxonomy.

His interests include driver safety, bicycling, running, the arts, web page development, meditation, and his dog and cat. He is also a member of the Human Factors and Ergonomics Society, the Society of Automotive Engineers, Division 21 of the American Psychological Association, the American Society of Safety Engineers, Alpha Pi Mu, and Psi Chi.