



SAfety VEhicles using adaptive Interface Technology (Task 8)

Intent Inference

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8.0 Program Overview

Driver distraction is a major contributing factor to automobile crashes. National Highway Traffic Safety Administration (NHTSA) has estimated that approximately 25% of crashes are attributed to driver distraction and inattention (Wang, Knipling, & Goodman, 1996). The issue of driver distraction may become worse in the next few years because more electronic devices (e.g., cell phones, navigation systems, wireless Internet and email devices) are brought into vehicles that can potentially create more distraction. In response to this situation, the John A. Volpe National Transportation Systems Center (VNTSC), in support of NHTSA's Office of Vehicle Safety Research, awarded a contract to Delphi Electronics & Safety to develop, demonstrate, and evaluate the potential safety benefits of adaptive interface technologies that manage the information from various in-vehicle systems based on real-time monitoring of the roadway conditions and the driver's capabilities. The contract, known as SAfety VEhicle(s) using adaptive Interface Technology (SAVE-IT), is designed to mitigate distraction with effective countermeasures and enhance the effectiveness of safety warning systems.

The SAVE-IT program serves several important objectives. Perhaps the most important objective is demonstrating a viable proof of concept that is capable of reducing distraction-related crashes and enhancing the effectiveness of safety warning systems. Program success is dependent on integrated closed-loop principles that, not only include sophisticated telematics, mobile office, entertainment and safety warning systems, but also incorporate the state of the driver. This revolutionary closed-loop vehicle environment will be achieved by measuring the driver's state, assessing the situational threat, prioritizing information presentation, providing adaptive countermeasures to minimize distraction, and optimizing advanced collision warning.

To achieve the objective, Delphi Electronics & Safety has assembled a comprehensive team including researchers and engineers from the University of Iowa, University of Michigan Transportation Research Institute (UMTRI), General Motors, Ford Motor Company, and Seeing Machines, Inc. The SAVE-IT program is divided into two phases shown in Figure i. Phase I spans one year (March 2003--March 2004) and consists of nine human factors tasks (Tasks 1-9) and one technology development task (Task 10) for determination of diagnostic measures of driver distraction and workload, architecture concept development, technology development, and Phase II planning. Each of the Phase I tasks is further divided into two sub-tasks. In the first sub-tasks (Tasks 1, 2A-10A), the literature is reviewed, major findings are summarized, and research needs are identified. In the second sub-tasks (Tasks 1, 2B-10B), experiments will be performed and data will be analyzed to identify diagnostic measures of distraction and workload and determine effective and driver-friendly countermeasures. Phase II will span approximately two years (October 2004--October 2006) and consist of a continuation of seven Phase I tasks (Tasks 2C--8C) and five additional tasks (Tasks 11-15) for algorithm and guideline development, data fusion, integrated countermeasure development, vehicle demonstration, and evaluation of benefits.

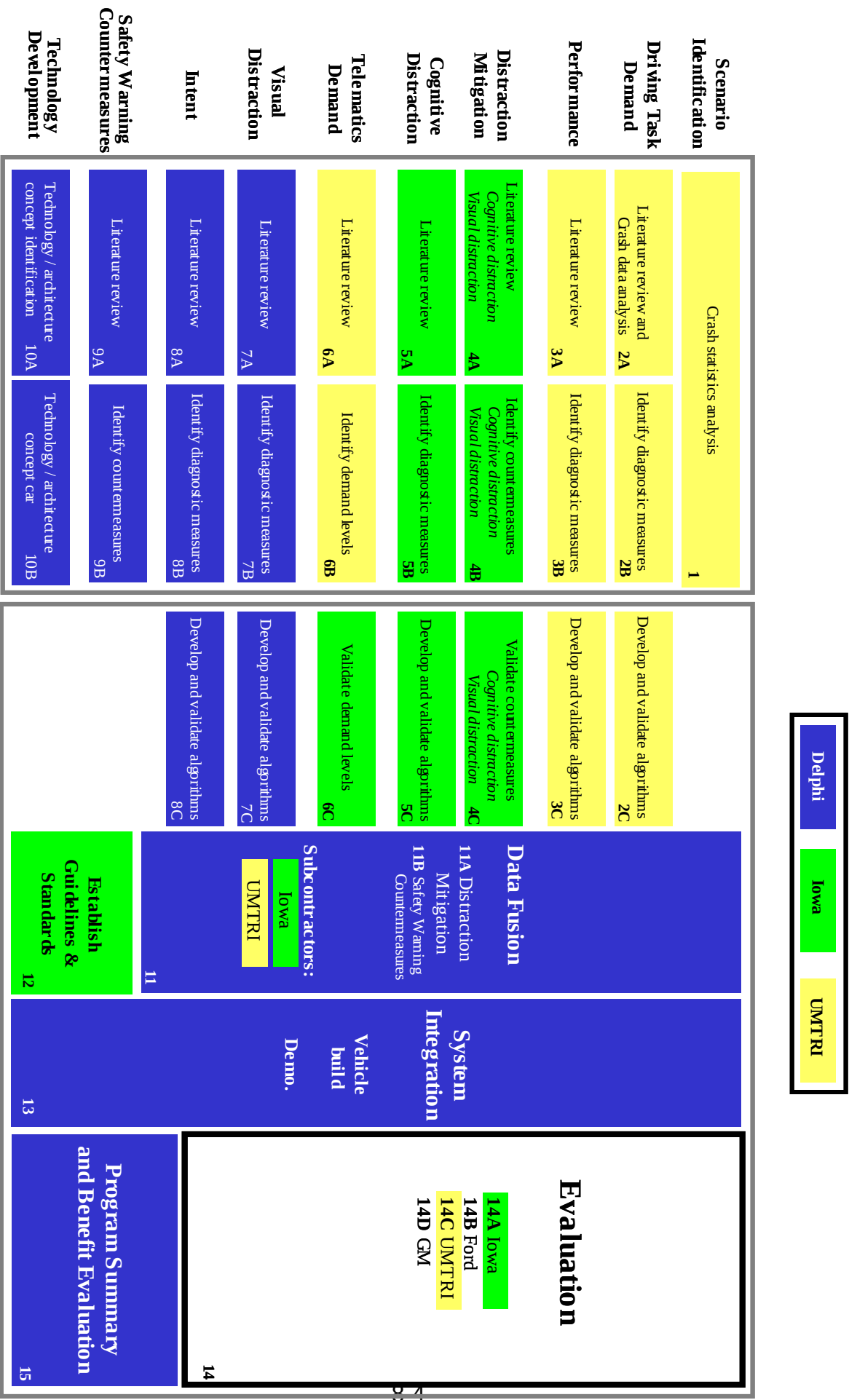


Figure i: SAVE-IT tasks

It is worthwhile to note the SAVE-IT tasks in Figure i are inter-related. They have been chosen to provide necessary human factors data for a two-pronged approach to address the driver distraction and adaptive safety warning countermeasure problems. The first prong (Safety Warning Countermeasures sub-system) uses driver distraction, intent, and driving task demand information to adaptively adjust safety warning systems such as forward collision warning (FCW) systems in order to enhance system effectiveness and user acceptance. Task 1 is designed to determine which safety warning system(s) should be deployed in the SAVE-IT system. Safety warning systems will require the use of warnings about immediate traffic threats without an annoying rate of false alarms and nuisance alerts. Both false alarms and nuisance alerts will be reduced by system intelligence that integrates driver state, intent, and driving task demand information that is obtained from Tasks 2 (Driving Task Demand), 3 (Performance), 5 (Cognitive Distraction), 7 (Visual Distraction), and 8 (Intent).

The safety warning system will adapt to the needs of the driver. When a driver is cognitively and visually attending to the lead vehicle, for example, the warning thresholds can be altered to delay the onset of the FCW alarm or reduce the intrusiveness of the alerting stimuli. When a driver intends to pass a slow-moving lead vehicle and the passing lane is open, the auditory stimulus might be suppressed in order to reduce the alert annoyance of a FCW system. Decreasing the number of false positives may reduce the tendency for drivers to disregard safety system warnings. Task 9 (Safety Warning Countermeasures) will investigate how driver state and intent information can be used to adapt safety warning systems to enhance their effectiveness and user acceptance. Tasks 10 (Technology Development), 11 (Data Fusion), 12 (Establish Guidelines and Standards), 13 (System Integration), 14 (Evaluation), and 15 (Program Summary and Benefit Evaluation) will incorporate the research results gleaned from the other tasks to demonstrate the concept of adaptive safety warning systems and evaluate and document the effectiveness, user acceptance, driver understandability, and benefits and weaknesses of the adaptive systems. It should be pointed out that the SAVE-IT system is a relatively early step in bringing the driver into the loop and therefore, system weaknesses will be evaluated, in addition to the observed benefits.

The second prong of the SAVE-IT program (Distraction Mitigation sub-system) will develop adaptive interface technologies to minimize driver distraction to mitigate against a global increase in risk due to inadequate attention allocation to the driving task. Two examples of the distraction mitigation system include the delivery of a gentle warning and the lockout of certain telematics functions when the driver is more distracted than what the current driving environment allows. A major focus of the SAVE-IT program is the comparison of various mitigation methods in terms of their effectiveness, driver understandability, and user acceptance. It is important that the mitigation system does not introduce additional distraction or driver frustration. Because the lockout method has been shown to be problematic in the aviation domain and will likely cause similar problems for drivers, it should be carefully studied before implementation. If this method is not shown to be beneficial, it will not be implemented.

The distraction mitigation system will process the environmental demand (Task 2: Driving Task Demand), the level of driver distraction [Tasks 3 (Performance), 5 (Cognitive Distraction), 7 (Visual Distraction)], the intent of the driver (Task 8: Intent), and the telematics distraction potential (Task 6: Telematics Demand) to determine which functions should be advised against under a particular circumstance. Non-driving task information and functions will be prioritized based on how crucial the information is at a specific time relative to the level of driving task demand. Task 4 will investigate distraction mitigation strategies and methods that are very well accepted by the users (i.e., with a high level of user acceptance) and understandable to the drivers. Tasks 10 (Technology Development), 11 (Data Fusion), 12 (Establish Guidelines and Standards), 13 (System Integration), 14 (Evaluation), and 15 (Program Summary and Benefit Evaluation) will incorporate the research results gleaned from the other tasks to demonstrate the concept of using adaptive interface technologies in distraction mitigation and evaluate and document the effectiveness, driver understandability, user acceptance, and benefits and potential weaknesses of these technologies.

In particular, driving task demand and driver state (including driver distraction and impairment) form the major dimensions of a driver safety system. It has been argued that crashes are frequently caused by drivers paying insufficient attention when an unexpected event occurs, requiring a novel (non-automatic) response. As displayed in Figure ii, attention to the driving task may be depleted by driver impairment (due to drowsiness, substance use, or a low level of arousal) leading to diminished attentional resources, or allocation to non-driving tasks¹. Because NHTSA is currently sponsoring other impairment-related studies, the assessment of driver impairment is not included in the SAVE-IT program at the present time. One assumption is that safe driving requires that attention be commensurate with the driving demand or unpredictability of the environment. Low demand situations (e.g., straight country road with no traffic at daytime) may require less attention because the driver can usually predict what will happen in the next few seconds while the driver is attending elsewhere. Conversely, high demand (e.g., multi-lane winding road with erratic traffic) situations may require more attention because during any time attention is diverted away, there is a high probability that a novel response may be required. It is likely that most intuitively drivers take the driving-task demand into account when deciding whether or not to engage in a non-driving task. Although this assumption is likely to be valid in a general sense, a counter argument is that problems may also arise when the situation appears to be relatively benign and drivers overestimate the predictability of the environment. Driving

¹ The distinction between driving and non-driving tasks may become blurred sometimes. For example, reading street signs and numbers is necessary for determining the correct course of driving, but may momentarily divert visual attention away from the forward road and degrade a driver's responses to unpredictable danger evolving in the driving path. In the SAVE-IT program, any off-road glances, including those for reading street signs, will be assessed in terms of visual distraction and the information about distraction will be fed into adaptive safety warning countermeasures and distraction mitigation sub-systems.

environments that appear to be predictable may therefore leave drivers less prepared to respond when an unexpected threat does arise.

A safety system that mitigates the use of in-vehicle information and entertainment system (telematics) must balance both attention allocated to the driving task that will be assessed in Tasks 3 (Performance), 5 (Cognitive Distraction), and 7 (Visual Distraction) and attention demanded by the environment that will be assessed in Task 2 (Driving Task Demand). The goal of the distraction mitigation system should be to keep the level of attention allocated to the driving task above the attentional requirements demanded by the current driving environment. For example, as shown in Figure ii, “routine” driving may suffice during low or moderate driving task demand, slightly distracted driving may be adequate during low driving task demand, but high driving task demand requires attentive driving.

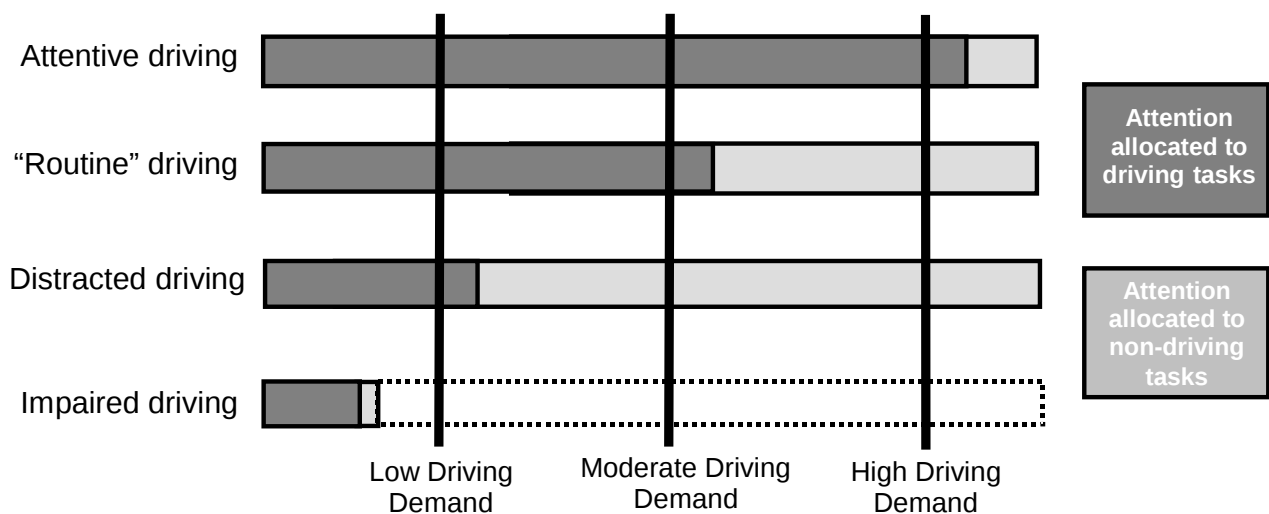


Figure ii. Attention allocation to driving and non-driving tasks

It is important to note that the SAVE-IT system addresses both high-demand and low-demand situations. With respect to the first prong (Safety Warning Countermeasures sub-system), the safety warning systems (e.g., the FCW system) will always be active, regardless of the demand. Sensors will always be assessing the driving environment and driver state. If traffic threats are detected, warnings will be issued that are commensurate with the real time attentiveness of the driver, even under low-demand situations. With respect to the second prong (Distraction Mitigation sub-system), driver state including driver distraction and intent will be continuously assessed under all circumstances. Warnings may be issued and telematics functions may be screened out under both high-demand and low-demand situations, although the threshold for distraction mitigation may be different for these situations.

It should be pointed out that drivers tend to adapt their driving, including distraction behavior and maintenance of speed and headway, based on driving (e.g., traffic and weather) and non-driving conditions (e.g., availability of telematics services), either consciously or unconsciously. For example, drivers may shed non-driving tasks (e.g., ending a cell phone conversation) when driving under unfavorable traffic and weather conditions. It is critical to understand this "driver adaptation" phenomenon. In principle, the "system adaptation" in the SAVE-IT program (i.e., adaptive safety warning countermeasures and adaptive distraction mitigation sub-systems) should be carefully implemented to ensure a fit between the two types of adaptation: "system adaptation" and "driver adaptation". One potential problem in a system that is inappropriately implemented is that the system and the driver may be reacting to each other in an unstable manner. If the system adaptation is on a shorter time scale than the driver adaptation, the driver may become confused and frustrated. Therefore, it is important to take the time scale into account. System adaptation should fit the driver's mental model in order to ensure driver understandability and user acceptance. Because of individual difference, it may also be important to tailor the system to individual drivers in order to maximize driver understandability and user acceptance. Due to resource constraints, however, a nominal driver model will be adopted in the initial SAVE-IT system. Driver profiling, machine learning of driver behavior, individual difference-based system tailoring may be investigated in future research programs.

Communication and Commonalities Among Tasks and Sites

In the SAVE-IT program, a "divide-and-conquer" approach has been taken. The program is first divided into different tasks so that a particular research question can be studied in a particular task. The research findings from the various tasks are then brought together to enable us to develop and evaluate integrated systems. Therefore, a sensible balance of commonality and diversity is crucial to the program success. Diversity is reflected by the fact that every task is designed to address a unique question to achieve a particular objective. As a matter of fact, no tasks are redundant or unnecessary. Diversity is clearly demonstrated in the respective task reports. Also documented in the task reports is the creativity of different task owners in attacking different research problems.

Task commonality is very important to the integration of the research results from the various tasks into a coherent system and is reflected in terms of the common methods across the various tasks. Because of the large number of tasks (a total of 15 tasks depicted in Figure i) and the participation of multiple sites (Delphi Electronics & Safety, University of Iowa, UMTRI, Ford Motor Company, and General Motors), close coordination and commonality among the tasks and sites are key to program success. Coordination mechanisms, task and site commonalities have been built into the program and are reinforced with the bi-weekly teleconference meetings and regular email and telephone communications. It should be pointed out that little time was wasted in meetings. Indeed, some bi-weekly meetings were brief when decisions can be made quickly, or canceled when issues can be resolved before the meetings. The level of coordination and commonality among multiple sites and tasks is un-precedented

and has greatly contributed to program success. A selection of commonalities is described below.

Commonalities Among Driving Simulators and Eye Tracking Systems In Phase I

Although the Phase I tasks are performed at three sites (Delphi Electronics & Safety, University of Iowa, and UMTRI), the same driving simulator software, Drive Safety™ (formerly called GlobalSim™) from Drive Safety Inc., and the same eye tracking system, FaceLab™ from Seeing Machines, Inc. are used in Phase I tasks at all sites. The performance variables (e.g., steering angle, lane position, headway) and eye gaze measures (e.g., gaze coordinate) are defined in the same manner across tasks.

Common Dependent Variables An important activity of the driving task is tactical maneuvering such as speed and lane choice, navigation, and hazard monitoring. A key component of tactical maneuvering is responding to unpredictable and probabilistic events (e.g., lead vehicle braking, vehicles cutting in front) in a timely fashion. Timely responses are critical for collision avoidance. If a driver is distracted, attention is diverted from tactical maneuvering and vehicle control, and consequently, reaction time (RT) to probabilistic events increases. Because of the tight coupling between reaction time and attention allocation, RT is a useful metric for operationally defining the concept of driver distraction. Furthermore, brake RT can be readily measured in a driving simulator and is widely used as input to algorithms, such as the forward collision warning algorithm (Task 9: Safety Warning Countermeasures). In other words, RT is directly related to driver safety. Because of these reasons, RT to probabilistic events is chosen as a primary, "ground-truth" dependent variable in Tasks 2 (Driving Task Demand), 5 (Cognitive Distraction), 6 (Telematics Demand), 7 (Visual Distraction), and 9 (Safety Warning Countermeasures).

Because RT may not account for all of the variance in driver behavior, other measures such as steering entropy (Boer, 2001), headway, lane position and variance (e.g., standard deviation of lane position or SDLP), lane departures, and eye glance behavior (e.g., glance duration and frequency) are also be considered. Together these measures will provide a comprehensive picture about driver distraction, demand, and workload.

Common Driving Scenarios For the tasks that measure the brake RT, the "lead vehicle following" scenario is used. Because human factors and psychological research has indicated that RT may be influenced by many factors (e.g., headway), care has been taken to ensure a certain level of uniformity across different tasks. For instance, a common lead vehicle (a white passenger car) was used. The lead vehicle may brake infrequently (no more than 1 braking per minute) and at an unpredictable moment. The vehicle braking was non-imminent in all experiments (e.g., a low value of deceleration), except in Task 9 (Safety Warning Countermeasures) that requires an imminent braking. In addition, the lead vehicle speed and the time headway between the lead vehicle and the host vehicle are commonized across tasks to a large extent.

Subject Demographics It has been shown in the past that driver ages influence driving performance, user acceptance, and driver understandability. Because the age

effect is not the focus of the SAVE-IT program, it is not possible to include all driver ages in every task with the budgetary and resource constraints. Rather than using different subject ages in different tasks, however, driver ages are commonized across tasks. Three age groups are defined: younger group (18-25 years old), middle group (35-55 years old), and older group (65-75 years old). Because not all age groups can be used in all tasks, one age group (the middle group) is chosen as the common age group that is used in every task. One reason for this choice is that drivers of 35-55 years old are the likely initial buyers and users of vehicles with advanced technologies such as the SAVE-IT systems. Although the age effect is not the focus of the program, it is examined in some tasks. In those tasks, multiple age groups were used.

The number of subjects per condition per task is based on the particular experimental design and condition, the effect size shown in the literature, and resource constraints. In order to ensure a reasonable level of uniformity across tasks and confidence in the research results, a minimum of eight subjects is used for each and every condition. The typical number of subjects is considerably larger than the minimum, frequently between 10-20.

Other Commonalities In addition to the commonalities across all tasks and all sites, there are additional common features between two or three tasks. For example, the simulator roadway environment and scripting events (e.g., the TCL scripts used in the driving simulator for the headway control and braking event onset) may be shared between experiments, the same distraction (non-driving) tasks may be used in different experiments, and the same research methods and models (e.g., Hidden Markov Model) may be deployed in various tasks. These commonalities afford the consistency among the tasks that is needed to develop and demonstrate a coherent SAVE-IT system.

The Content and Structure of the Report

The report submitted herein is a final report for Task 8 (Intent) that documents the research progress to date (March 2003-March 2004) in Phase I. In this report, the major results from the literature review are summarized to determine the research needs for the present study, the experimental methods and resultant data are described, diagnostic measures and preliminary algorithms are identified, and human factors recommendations are offered.

8.1 INTRODUCTION

The objective of Task 8 (Intent) is to determine a set of diagnostic indicators that support the inference of host-driver intentions such that the intended maneuver can be predicted before it is initiated. Driver intent information could potentially benefit both the "Distraction Mitigation" and "Safety Warning Countermeasures" sub-systems. In the "Distraction Mitigation" sub-system, knowledge of driver intent may be used to suppress unnecessary non-driving task activity before and during highly demanding driving maneuvers. For example, if a system can identify an intention to pass, it might screen phone calls while the driver executes the maneuver, negating the source of distraction during a perceptually demanding task. In the "Safety Warning Countermeasures" sub-system, suppressing alerts during certain driving maneuvers may offer the potential of reducing a large percentage of nuisance alerts, which could greatly improve driver acceptance of the system. There are several scenarios of lane-transition that can lead to nuisance alerts for the FCW system, including approaching to pass, turning, or changing lanes. A system that can reliably identify intents to pass, change lanes, or turn could suppress alerts that precede the predicted maneuver.

Task 8 (Intent) conducted a literature review and summarized the major methods and findings in Task 8A literature review report. The report cites previous studies to illustrate the potential application of intent detection in both the "Distraction Mitigation" and "Safety Warning Countermeasures" sub-systems.

Based on the literature review, a matrix (Table 8.1) was developed that organized the potentially diagnostic sources of information as a function of the type of maneuver that is intended. The potentially diagnostic sources of information have been organized into five categories, including affordances, motive, kinematics, controls, and eye fixations. Affordances constrain the possible actions that will be performed by the driver. For example, it is unlikely that a driver intends to turn in the immediate future if there is nowhere for the driver to turn. The motive category includes information regarding the FCW alert level, the range and range-rate to the lead vehicle, and navigation information. These sources of information may provide a reason for why the host vehicle will engage in a maneuver. It is likely that the driver must have already begun to execute the maneuver for kinematic variables to be diagnostic. For example, the yaw-rate may begin to change as a lane-change maneuver is initiated. Monitoring driver controls, including the gas and brake pedals, steering-wheel angle, and turn signals, may provide useful information for the inference of intent. For example, a sudden release of the gas pedal might indicate that the driver intends to brake or is about to engage in an avoidance maneuver. Fixation data such as mirror sample/head turns and forward-scene sampling are likely to be useful for the inference of all types of intent.

Table 8.1. Hypothesized diagnostic measures for intent detection

		Avoidance	Pass	Turn	Merge	Change lane	Brake
Affordances	Exit Ramps				•	•	
	Cross Streets		•	•	•	•	•
	Lane location and number		•	•	•	•	
Motive	FCW alert level	•					•
	Range to lead vehicle	•	•			•	•
	Range-rate to lead vehicle	•	•			•	•
	Navigation information			•	•	•	
Kinematics	Lead vehicle azimuth	•	•	•	•	•	
	Heading/Yaw Rate	•	•	•	•	•	
	Lateral Position	•	•	•	•	•	
	Speed / Acceleration	•	•	•	•	•	•
Controls	Gas pedal	•	•	•	•	•	•
	Brake pedal	•		•	•	•	•
	Steering-wheel angle	•	•	•	•	•	
	Turn signal	•	•	•	•	•	
Fixation	Mirror sampling / head turn	•	•	•	•	•	
	Forward-scene sampling	•	•	•	•	•	•

Note—Black circles represent that the measure may potentially be diagnostic for the given type of intent.

8.2 THE NATURALISTIC LANE CHANGE DATA SET

The original plan for this task was to use the data that was collected in Task 3 (Performance). During the initial planning phases, we had anticipated that the Task 3 data collection activity would be less constrained and more naturalistic. However, in order to examine the effects of distraction on driving performance on real roadways, Task 3 manipulated the levels of distraction in a highly scripted and constrained manner. The demands of safety and of producing high levels of distraction, combined with the short time span of Task 3b, dictated an experiment wherein the driver was accompanied with an experimenter and events that were manipulated in an orderly and highly-constrained fashion. Therefore the data set that was collected for Task 3 did not represent the naturalistic data set that was anticipated. Instead, the data set included few maneuvers on relatively homogeneous roadway segments, while drivers were instructed to engage in highly-distracting tasks. The reason that it is so important that the driver be unconstrained in this task is that driver behaviors relating to maneuvers such as lane changes are likely to be extremely sensitive to the constraints of the experiment. For example, if these subjects feel like their driving performance is being evaluated, they may be more inclined to engage in more courteous and rule-following behaviors such as using the turn signal or changing one lane at a time. Lane change behaviors are also likely to be quite sensitive to the complexity of the environment and the motive of the driver to arrive at the destination in a timely manner.

The fact that the Task 3 data set included virtually no lane changes or other maneuvers in which Task 8 (Intent) might be interested all but ruled out using the Task 3 data set for Task 8. During the initial work of Task 8b, however, we anticipated that we might be able to use some segments of the Task 3 data set for examining null-intent cases (cases wherein a maneuver did not occur). In order to determine whether an algorithm or measure is diagnostic, we need to investigate both false negatives (on cases wherein a maneuver did occur) and false positives (on cases wherein a maneuver did not occur). As it became increasingly apparent that the Task 3 data set was highly-constrained and that the periods of “normal” driving were just intervals between distraction events, the notion of using the Task 3 data set for Task 8 analyses was abandoned. The behaviors during these “null” segments are likely to be far less complex than the range of behaviors that occur in less constrained driving situations.

During the initial phases on this task, several naturalistic data sets from prior studies were considered. The first of these studies was the ICC (Intelligent Cruise Control) FOT study. A precursor to the ACAS FOT (Advanced Collision Avoidance Systems Field Operational Test) program, the ICC FOT examined the performance of vehicles that were equipped with adaptive cruise control systems. However, because the Task 8 (Intent) literature review revealed that eye fixation data were likely to be crucial for a comprehensive intent-inference analysis and because the ICC FOT data set did not include any fixation data or facial video recordings, using the ICC FOT data set was ruled out. The ACAS FOT data set was ruled out for a similar reason. Although the ACAS FOT data set did include facial video, this video was collected only intermittently (when triggered by certain ACAS-relevant events) or was sampled at lower temporal and spatial resolution during intermittent intervals. The quality of the video was insufficient for a frame-by-frame analysis of the driver’s precise fixation

location. Whereas the ACAS FOT facial video afforded an intermittent and coarse analysis of eyes-forward versus eyes-off-road, it did not afford a more precise analysis of whether the driver was gazing at a side-view mirror or speedometer.

The final data set that was considered was the Naturalistic lane change study, conducted by Virginia Tech Transportation Institute (VTTI), with funding provided by the National Highway Traffic Safety Administration (NHTSA). This project was led by Suzanne Lee and involved the collection of the naturalistic driving data of sixteen commuters in the southwestern region of Virginia spanning October 2000 to July 2001 and was included in the Lee, Olsen, and Wierwille (2004) report to NHTSA. The purpose of this study was to examine the natural lane-change behaviors of drivers of passenger vehicles (half of the drivers drove a sedan and half drove an SUV). One major advantage of this data set is that these researchers were actually focusing on the lane-change events, and the data set had already been reduced accordingly. Although the purpose of their analyses (understanding lane change behavior) were different from the purpose of Task 8 (predicting lane changes), the overlap between these two objectives is quite fortuitous and the reduced data set represented a manageable set of data that could be analyzed for Task 8 (Intent). Not only did this data set include facial video, but also it had already been reduced (frame-by-frame) to provide the fixation locations during the 3-s prior to each lane-change maneuver.

The drivers of this study were of ages ranging from 20 to 64 ($M = 40.8$, $SD = 12.2$), and half were male and half were female. An additional selection criterion was that these drivers must commute for more than 25 miles in each direction. Half of these drivers commuted on the I-81 interstate and the other half commuted on either U.S. 460 or U.S. 11 (mostly 2-lane in each direction). These drivers were unaccompanied during data collection and data collection occurred during their drives to and from work.

The complete Lane Change data set included 8667 lane changes performed over 23,949 miles of data collection. The 182 tapes of video data and 24 GB of raw sensor data represent an effort that is beyond the resources of the Phase I Intent Task. Although VTTI conducted some analyses on the entire set of 8667 lane changes, the in-depth analyses focused on a set of 500 lane changes. The sampling of the full data set down to the in-depth data set was biased toward lane-changes of higher severity and urgency ratings. The eye fixation analyses were conducted on the reduced set of lane changes. VTTI analyzed the driver's fixations at 100 msec intervals during the 3-s prior to the initiation of each lane change (defined as the point at which the vehicle first moved laterally). VTTI coded these fixations according to the following set of glance locations:

- Center forward (CF)
- Left forward (LF)
- Right forward (RF)
- Rearview mirror (RVM)

- Left mirror (LM)
- Left window (LW)
- Left blind spot (LBS)
- Instrument cluster (IC)
- Right mirror (RM)
- Right window (RW)
- Right blind spot (RBS)
- Other interior (O)

It became increasingly apparent that the in-depth data set containing the 500 naturalistic lane changes was an extremely relevant and useful set of data for determining diagnostic measures of driver intent to change lanes. Through working with our mutual sponsor (NHTSA), the SAVE-IT program was able to acquire this data set from VTTI for the purpose of subsequent analyses of driver intent inference. It is important to point out that although VTTI collected and reduced this data set, they were in no way involved in this subsequent intent-related data analysis for the SAVE-IT program. The results of these analyses contained in this report do not reflect the work or views of VTTI.

Although this data set is extremely useful for this task and represents the sole focus of Phase I activity, there are some limitations of this data set for intent-inference work. The major limitation is that it involves a set of lane changes and does not include a set of events where lane changes did not occur. Because VTTI were focused on understanding the nature of lane changes, rather than on developing an algorithm that can predict lane changes, their data reductions were focused solely on events where the host vehicle did change lanes. Whereas this data set provides a unique opportunity for evaluating an algorithm with respect to true positives (correct prediction of a lane change when one does occur) and false negatives (failure to predict a lane change when one does occur), it does not afford an analysis of false positives (false prediction of a lane change when one does not occur) and true negatives (correct prediction that no lane change will occur when one does not occur). Without the null cases, Phase I was unable to provide validated diagnostic algorithms for the detection of driver intent. Instead Phase I concludes with a set of promising candidate measures which appear to precede and coincide with lane changes. The validation of these measures and the determination of diagnostic measures must therefore reside in Phase II. The other potential limitation is that the glance measures only extend 3 s prior to the initiation of lane change. At this time, it is not known whether this time interval is of sufficient length. Once again, this limitation suggests that further work is required in Phase II.

The following section (Section 8.3: Intent Detection Framework) will discuss the framework that was developed for detecting a driver's intent to change lane and some general findings of the lane-change data analyses. Section 8.4: Lane Change Maneuver Results) will

discuss the results of the analyses with respect to the different types of lane change maneuvers

8.3 INTENT DETECTION FRAMEWORK

After reviewing the literature in Phase I and during the preliminary analyses of the lane-change data set, a framework for the intent-inference problem began to emerge. This framework represents a division of different types of information to which a vehicle may have access and proposes a way of parsing the intent-inference problem into four separate modules. Although this framework was developed in response to the lane-change data, it is likely to be effective for the detection of other types of maneuvers. This intent-inference framework proposes that the problem be divided into the following four modules:

- **Motive**
 - The motive module asks the question: “Is there a reason for the driver to engage in a specific maneuver?” (e.g., the host vehicle is quickly approaching a slower lead vehicle)
- **Affordance**
 - The affordance module asks the question: “Does the environment afford the specific maneuver to be executed at this time?” (e.g., if there is no left lane present, it is unlikely that the driver intends a left lane change)
- **Pre-maneuver Behavior**
 - The pre-maneuver behavior module asks the question: “Are there any behavioral indicators that suggest that the driver is intending a maneuver?” (e.g., frequent glances at the blind spot or side view mirror)
 - This module uses the data sources from Table 8.1 that could include kinematics, controls, and fixation.
- **Maneuver Execution**
 - The maneuver-execution module asks the question: “Is there evidence that the driver has begun to engage in a maneuver?” (e.g., sudden steering wheel movement)
 - This module uses the data sources from Table 8.1 that could include kinematics, controls, and fixation.

This section will discuss these intent-inference modules in more detail.

8.3.1 Motive

The motive module focuses entirely on the environment surrounding the host vehicle. One of the most striking results of VTTI's data analysis was that it revealed that lane changes occur for a relatively small set of reasons. Rather than changing lanes randomly, drivers tend to make lane changes in response to specific environmental and goal-oriented circumstances. The exception to this rule is that some lane changes are unintentional (Lee et al. revealed that 0.8 percent of their 8667 lane changes were unintended), perhaps arising from driver inattention or drowsiness. Because this task focuses on detecting driver intention, unintended lane changes are beyond the scope of this project, and instead will be considered by lane departure warning systems (Task 9: Safety Warning Countermeasures). The VTTI data analyses further revealed that a relatively small set of motives is able to account for a large proportion of lane changes.

Table 8.2. Motives for Lane-changes and turn-signal usage

Motive for Lane-Change Maneuver	Direction of Lane-Change	Percentage* of total Lane Changes	Cumulative Percentage*	Number of events in data set**	Probability of using turn-signal
Slow Lead Vehicle	Left	34	34	267	0.46
Return	Right	17	52	35	0.11
Preparation to Exit	Right	17	69	50	0.48
Enter Highway	Left	6	76	23	0.59
Preparation to Exit	Left	6	82	22	0.68
Tailgating Rear Veh.	Right	4	86	15	0.40
Slow Lead Vehicle	Right	3	89	27	0.34
Merging Lead Veh.	Left	3	92	17	0.94
Entry to Highway	Right	1	93	6	0.67
Lane Drop	Left	1	94	9	0.22
Lane Drop	Right	1	95	6	0.50

* The percentages and cumulative percentages are based on VTTI's analysis of the entire set of 8667 lane changes.

** The number of events in data set refers to the number of events in the 500 in-depth data set that Task 8 (Intent) has available for analysis.

Table 8.2 displays the results of VTTI's analyses of the different types of lane changes. The cumulative percentage of the 8667 lane changes reveals that 92 percent of lane changes are motivated by either a slow lead vehicle, a return to an original lane, preparation to exit, entry to a highway, a tailgating rear vehicle, or the presence of a merging lead vehicle. The major insight that can be gained from this analysis is that a great deal of information can be gained about whether a driver is about to engage in a lane-change maneuver just by examining the environment surrounding the host vehicle. Note also that the usage of turn signals varies as a function of the different motivating factors. For example, drivers used the turn signal on average 11 percent of the time during a return to the original lane compared with 94 percent of the time during a left lane change motivated by an inbound merging lead vehicle. This suggests that the turn signal alone is an extremely reliable indicator of lane changes that are motivated by a merging lead vehicle. No further resources need be

allocated to this particular type of lane change. However, the turn signal is not a reliable indicator of the remaining types of lane changes.

The types of sensors that could provide useful motive information vary across the different types of lane changes. For the detection of lane changes that are motivated by slow lead vehicles (representing 37 percent of the total), sensors that can detect the range and range-rate of the lead vehicle (e.g., laser or radar) would be useful. For extreme cases of a host vehicle being tailgated, a rear looking sensor for the purposes of back-up aid could potentially be useful, however, on most vehicles, the range of a back-up aid or park assist sensor would likely be too short for all but the most extreme cases of tailgating. For the motives that involve a change in the state of the roadway (e.g., entry to a highway or lane drop), a GPS/map-matching system could provide useful data. If the presence of a lane-drop can be detected, then this would provide an almost perfect indication that a lane change is about to occur. The motive of preparation to exit could be detected by a combination of a GPS/map-matching system and a system that provides some indication of the route that the driver is following. Navigation systems (if present) or an algorithm that analyzes the prior history of the driver's maneuvers (e.g., if a driver usually has exited at a given exit, this could be a good predictor of a motive for preparation to exit) could potentially provide route information. A system that has recently detected a left lane change in combination with data that suggests that the right lane is now unobstructed could provide evidence that a motive to return to the original lane exists.

In some circumstances, motive information alone may be a sufficient predictor of lane changes (e.g., a lane drop), however, in other cases (e.g., return to original lane) the motive module should be combined with information from the other modules for a more reliable intent-inference algorithm.

8.3.2 Affordance

Gibson (1979/1986) invented the term “affordance” from the verb “to afford”, defining affordances as “what it [the environment] offers animals, what it provides or furnishes, either for good or ill.” As Takahashi (2000) demonstrated in his studies of intent detection, affordances constrain the possible actions that will be performed by the driver and thus may provide a useful indication of whether a maneuver is likely to occur. In the case of lane-changes, affordances can provide useful information regarding the likelihood of a lane change maneuver because in many situations a lane change is not possible. For example, the motive module may detect that the host vehicle is rapidly approaching a lead vehicle and therefore arrive at the conclusion that the driver has motive to perform a left lane change to avoid a lead vehicle. However, if the left lane is completely obstructed by a constant flow of traffic, or if no left lane currently exists (e.g., in construction) then the affordance module may override the information of the motive module.

In some circumstances the line dividing affordances from motives may appear to be quite narrow. For example, an upcoming exit may provide both a motive to change lanes and an opportunity/affordance to exit the highway. Another example is that an unobstructed right

lane provides the motive to engage in a return to the original lane and provides an opportunity to do so. However, to clarify the distinct existence of these modules, the affordance module assesses whether a left or right lane change is physically possible or legally permissible in the immediate future. Whether this left or right lane change is likely to benefit the driver in the near future is not relevant to the affordance module and resides solely within the motive module.

The affordance module could benefit greatly from a GPS/map-matching system that can inform this module about whether a target lane exists into which to change. Alternatively, this information could be provided by a vision system that processes the images of a forward-looking camera (e.g., a lane tracking system). If a lane is present, the next question addresses whether or not the lane is obstructed by another vehicle. A side-obstacle detection system could provide this information in most cases (when the approaching vehicle is either closing in slowly not at all). If such a sensor is not present, then a temporal extrapolation of the data from a forward-looking radar may be able to predict that a vehicle is currently occupying the space that the intended maneuver would otherwise move the host vehicle toward. For example, the range rate of vehicle that is being passed (measured by the forward-looking radar or laser sensor) could be extrapolated for several seconds after it is beyond the detection angle (azimuth) of the sensor to predict when it has been passed.

The affordance module in isolation is unlikely to reliably infer lane-change intentions. To know that a lane change is possible is not the same as knowing that a lane change is about to occur. Lee et al. (2002) discovered that lane changes only occur once every 2.76 miles in their data set. Therefore, there is likely to be a great deal of mileage during which a lane change is possible but does not occur. However, to know that a lane change is impossible is almost equivalent to knowing that a intentional lane change is not about to occur (unless the driver is not aware that the lane change is not possible). Therefore the affordance module may provide a powerful means of ruling out the possibility of a lane change in the near future and thus provide additional protection against false positives.

8.3.3 Pre-maneuver Behaviors

Unlike the previous two modules (motive and affordance), the pre-maneuver behaviors module analyzes the behavior of the driver-vehicle system to determine whether a lane change is likely. This module is likely to rely most heavily on glance location and transition measures but some control variables (e.g., turn signal) are also likely to be useful. Unlike the execution-indicator module, the pre-maneuver behaviors module focuses solely on behaviors that occur prior to the initiation of the lane-change event (which Lee et al. defined as the point at which the vehicle first begins to move laterally).

The most obvious indicator of driver intention is the turn signal. Whereas this may provide a reliable indication of lane-change intent during some types of maneuvers (e.g., merging lead vehicle), for most maneuvers it does not provide a satisfactory basis for the prediction of lane changes. However, the turn signal may be used in conjunction with other types of measures to provide a reliable indicator of driver intent. Because the driver must collect

information about whether a lane change will be beneficial to their driving task (motive) and can be conducted safely or legally (affordance), it is reasonable to expect that the focus of the drivers visual attention will vary in characteristic and potentially diagnostic patterns prior to the execution of a lane change. The literature review portion of this task revealed several studies in which such eye-fixation or transition behaviors were observed (e.g., Mourant and Donahue, 1974). Lee et al. (2004) also revealed that the pattern of fixations varies depending on the type of lane change, including both the left versus right distinction and the motive distinctions that were discussed previously in this section. For this reason, the glance transitions will be discussed in more detail in the next section (8.4: Specific Lane Change Results) within the different types of lane changes.

Table 8.3 displays the results of a glance location analysis as a function of lane change motive and direction. The number of cases in which the driver glanced at the specified locations and the amount of time (in msec) that the driver spent glancing at each location were tabulated for slow lead vehicle left and right, preparation to exit left and right, tailgating rear vehicle right, and return to original lane right lane changes. The gray highlights in this table represent glance locations that appear to be relevant for acquiring information that is pertinent to the lane change.

In the absence of a null data set in which no lane changes were made it is impossible to determine whether these patterns of fixations will be diagnostic of particular maneuvers. However, we can superficially compare these data with those of Mourant and Donahue (1974) who also collected data on real roadways, consistent with their own comparison. From this comparison it is evident that the percentage of time spent sampling the two relevant mirrors (see “total of 2 mirrors” in Table 8.3) in the Lee et al. data set (3-s prior to initiating the maneuver) is larger than that of Mourant and Donahue’s null data set, where the average was 5 percent (assuming an average speed of 45 mph). The percentage of time sampling the two relevant mirrors ranges from 15 (Slow lead vehicle right) to 32 percent (Tailgating rear vehicle right). Carter and Laya (1998) also have stated (based on both driving simulator and on-road studies) that during normal lane maintenance, drivers typically spend 70 percent of the time looking toward the focus of expansion and 15 percent of the time looking toward the instrument cluster. The 85 percent of glances during normal lane maintenance directed toward either the center forward (focus of expansion) and instrument cluster suggested by their work can be compared to that of the six types of lane changes displayed in Table 8.3. In this table, it is evident that the percentage of time spent looking at either the center forward (CF) or instrument cluster (IC) is far less during the 3 s prior to these lane changes, ranging from 42 (Preparation to exit left) to 67 (Preparation to exit right) percent. This large reduction in time spent looking at either the center forward (CF) or instrument cluster (IC) is consistent with Carter and Laya’s (1998) analyses.

Table 8.3. Glance Location Counts and Times as a function of Lane Change Motive and Direction During the 3-s Prior to Lane Change Initiation

			IC	O	LBS	LW	LM	LF	CF	RVM	RF	RM	RW	RBS	Total of 2 mirrors ¹	Total of gray regions ²	IC or CF
Slow Lead Vehicle Left	Cases	Total: 267 % of Total	52	4	69	89	135	76	262	138	14	6	1		215	240	262
			19		26	33	51	28	98	52	5				81	90	98
	Time (msec)	average % of Total	75		93	175	306	154	1490	289	22				594	862	1564
Preparation to exit Left	Cases	Total: 22 % of Total	4		5	9	19	5	21	7	2	3			22	22	21
			18		23	41	86	23	95	32	9	14			100	100	95
	Time (msec)	average % of Total	45		95	191	686	77	1214	136	100	50			823	1109	1259
Slow Lead Vehicle Right	Cases	Total: 27 % of Total	1					26	15	6		5	2	3	15	18	26
								96	56	22		19	7	11	56	67	96
	Time (msec)	average % of Total						1922	370	219		70	56	74	441	570	1922
Preparation to exit Right	Cases	Total: 50 % of Total	4		1	1	1	4	50	23	10	9	4	7	29	31	50
			8					8	100	46	20	18	8	14	58	62	100
	Time (msec)	average % of Total	48					72	1972	350	76	94	38	68	444	550	2020
Return to Original Lane Right	Cases	Total: 35 % of Total	4	2		1	2	7	35	25	6	8	5		27	29	35
			11	6			6	20	100	71	17	23	14		77	83	100
	Time (msec)	average % of Total	49	31			31	114	1797	380	63	109	86		489	411	1846
Tailgating Rear Vehicle Right	Cases	Total: 15 % of Total	1	1			2	2	15	15	3	2	2	2	15	15	15
							13	13	100	100	20	13	13	13	100	100	100
	Time (msec)	average % of Total					27	100	1307	920	107	40	53	80	960	1093	1307
	Cases	Total: 15 % of Total	1	1			2	2	15	15	3	2	2	2	15	15	15
							13	13	100	100	20	13	13	13	100	100	100
	Time (msec)	average % of Total					27	100	1307	920	107	40	53	80	960	1093	1307
	Cases	Total: 15 % of Total	1	1			2	2	15	15	3	2	2	2	15	15	15
							13	13	100	100	20	13	13	13	100	100	100
	Time (msec)	average % of Total					27	100	1307	920	107	40	53	80	960	1093	1307

Note: The first row represents the glance locations (using the abbreviations on pages 8.14 – 8.15). Zeroes and negligible numbers (e.g., when 1 is in the numerator) have been omitted to provide focus on the relevant areas of the table. In the event that there is more than one glance at the region, the case is only counted once so the number of cases refers to those in which the driver glanced at the region at least once. The rows that are labeled “time (msec)” reveal the average amount of the 3000-msec window prior to the event initiation that the driver spends glancing at the specified location.

1. The column labeled “Total of 2 mirrors” counts the number of cases in which the driver glances at either the rear view mirror or the mirror pertaining to the direction of the lane change at least once. This is not equivalent to the addition of the RVM and relevant mirror cells because cases in which the driver looks at both are only counted once.

2. The column labeled “Total of gray regions” counts the number of cases in which the driver glances at one of the regions highlighted in gray (a region that is relevant to this particular type of lane change) at least once. This is not equivalent to the addition of the gray cells because cases in which the driver looks at more than one region are only counted once.

This task also examined whether kinematic and control parameters could be used to help infer lane-change intent prior to execution. A simple analysis, comparing left lane changes to right lane changes, revealed that there were no reliable indicators (other than the turn-signal) that a driver is about to change lanes. Unless kinematic and control variables vary between lane changes as a whole (independent of direction or motive) and non-lane changes, which could not be examined in this data set, this analysis suggests that there are no reliable kinematic or control measures that can indicate that a lane change is about to occur. This conclusion is consistent with the analyses of Lee et al. (2004) on the same data set. However, Lee et al. did observe differences in the speeds between the different types of lane changes, e.g., “Tailgating lane changes” occurred at an average speed of 67 mph compared with “Enter lane changes” at an average speed of 47 mph.

8.3.4 Execution Indicators

Unlike the other three modules that attempt to detect a lane change before it actually occurs, this module attempts to detect a lane change as it is occurring. Because these sources of information are indicators of the maneuver rather than the intention to engage in the maneuver, this module is somewhat beyond the scope of Task 8 (Intent). The problem of detecting a maneuver as it occurs is actually the same problem that manufacturers of lane tracking systems focus on. These systems use a forward-looking camera and image processing algorithms to detect the driver's position in the lane. Companies such as Mobile Eye and Iteris already have a product on the market that serves this function. The outcome of SAVE-IT Tasks 1 (Scenario Identification) and 9 (Safety Warning Countermeasures) indicate that it is likely that the SAVE-IT vehicles are likely to include a lane departure warning system. There are many reasons to expect that image processing is likely to offer a more effective alternative to detecting lane change executions than kinematic and control variables. Based on Lee et al.'s (2004) analysis of their lane change data set, they reported that much of the kinematic or control data such as steering wheel angle and lateral acceleration was not diagnostic of a lane change even during the execution of the maneuver, stating (p. 79):

An analysis of numerous cases revealed that generally there is no obvious pattern for lane change in steering data. These data are quite noisy, possibly due to road crown, road curvature, road irregularities, wind, or driver failure to maintain center lane position... In most cases, such as that shown in Figure 4.3, the entire trace is very noisy with no discernable pattern... Using steering traces as indicators for lane changes could be very misleading and result in unacceptably high numbers of false alarms for a lane change CAS...As was true for the steering data, analysis of numerous cases revealed that most of the time there is no "telltale" pattern for lane changes in the lateral acceleration data.

After a cursory analysis of their data set of maneuver executions, there was even no obvious way to diagnose left lane changes from right lane changes using these parameters. This finding is in stark contrast to the work of Salvucci and colleagues (e.g., Salvucci, Boer, & Liu, 2001; Salvucci & Liu, 2002; Salvucci, 2004), who demonstrated that kinematic and control variables could support the reliable detection of a maneuver shortly after it was begun. Perhaps the most likely explanation for this discrepancy is that the work of Salvucci and colleagues was carried out in a driving simulator. Whereas the driving simulator may be a useful tool for studying many phenomena, other phenomena may be less amenable to the driving simulator. In the case of driver intention, intricate "normal-driving" behaviors are the focus of the research and the driver's interaction with the controls and dynamics of the vehicle and environment are paramount. It is therefore crucial that the data-collection environment is as close to that of the true phenomena as possible. This problem may be further amplified in Salvucci & Liu (2002) by researchers asking participants to state when they were about to change lanes, which could make drivers self-conscious and perform exaggerated, artificial, and potentially unrealistic behaviors. This places participants in the difficult psychological position of "driving how you normally would" where they must attempt to recollect how they would normally behave in a similar yet real situation. Therefore, it is

more likely that the naturalistic data set of Lee et al. (2004) is a more accurate reflection of reality than the data that Salvucci and colleagues based their algorithms.

Given that it is likely that lane tracking systems will provide superior detection of lane change executions than an algorithm based on kinematic and control variables, maneuver execution variables are defined as being outside the scope of this task. The objective of this task is therefore the challenging problem of inferring driver intentions and thereby predicting maneuvers before they actually occur. To the extent that the detection of lane position is useful in the SAVE-IT program, vision-based lane-tracking systems will be utilized to provide this source of information.

8.4 SPECIFIC LANE CHANGE RESULTS

Lee et al.'s (2004) analysis of the naturalistic lane change data revealed that a relatively small number of motives can account for a large proportion of the total lane changes. Because the dynamics of lane changes differ based on both the direction of the lane change and on the motive for changing lanes, the eye glance analyses of Task 8 (Intent) were conducted separately for each type of lane change. Several types of lane changes were selected for this analysis based on the prevalence of the lane change type, the number of cases in the data set that were available, and the inability to predict the lane change using simple criteria. Highway Entry and Lane Drop lane changes were not included because they account for a relatively small proportion of the total lane changes (combined 9 percent) and are likely to be best predicted by knowing where the vehicle is located. A GPS/map-matching system with sufficient data should be able to predict these types of lane changes with great success. The other type of lane change that was not included in the analyses was the lane changes in response to a merging lead vehicle because the lane change data set demonstrated that the turn signal is a reliable predictor of these events (94 percent of these lane changes were signaled). The selected set of lane changes account for 83 percent of the total 8667 lane changes and include slow lead vehicle left and right, preparation to exit left and right, tailgating rear vehicle right, and return right lane changes. This section will present the results of the data analyses for these specific types of lane changes.

8.4.1 Slow Lead Vehicle

The slow lead vehicle lane changes are motivated by the host vehicle approaching a slower lead vehicle. As the host vehicle closes in on the lead vehicle, the driver is faced with a decision of either slowing down and thus being constrained by the speed of the lead vehicle or maneuvering around the lead vehicle. When choosing the latter option, the driver engages in a slow lead vehicle change. Lane changes that are motivated by slow lead vehicles account for over 37 percent of the lane changes collected in the naturalistic lane change study and constitute the single largest category.

In order to quantify this motive based on the naturalistic lane change data, Task 8 (Intent) analyzed the minimum time-to-contact (s) and minimum time-headway (s) during the 3-s prior to when the maneuvers were initiated. Figure 8.1 displays the minimum time-to-contact (s) as a function of minimum time-headway (s) during the 3-s prior to when the maneuvers were initiated for the slow lead vehicle lane changes to the left. The horizontal line represents a time-to-contact criteria of 15 s and the vertical line represents a time-headway criteria of 1 s. The combined area of these two criteria bound 79% of the 265 cases of left slow lead vehicle lane changes. These data appear to indicate that drivers tend to use both criteria depending on the circumstance. In short, drivers are motivated to change lanes either because the lead vehicle is too close (time-headway) OR because the host vehicle is closing on the lead vehicle too rapidly (time-to-collision).

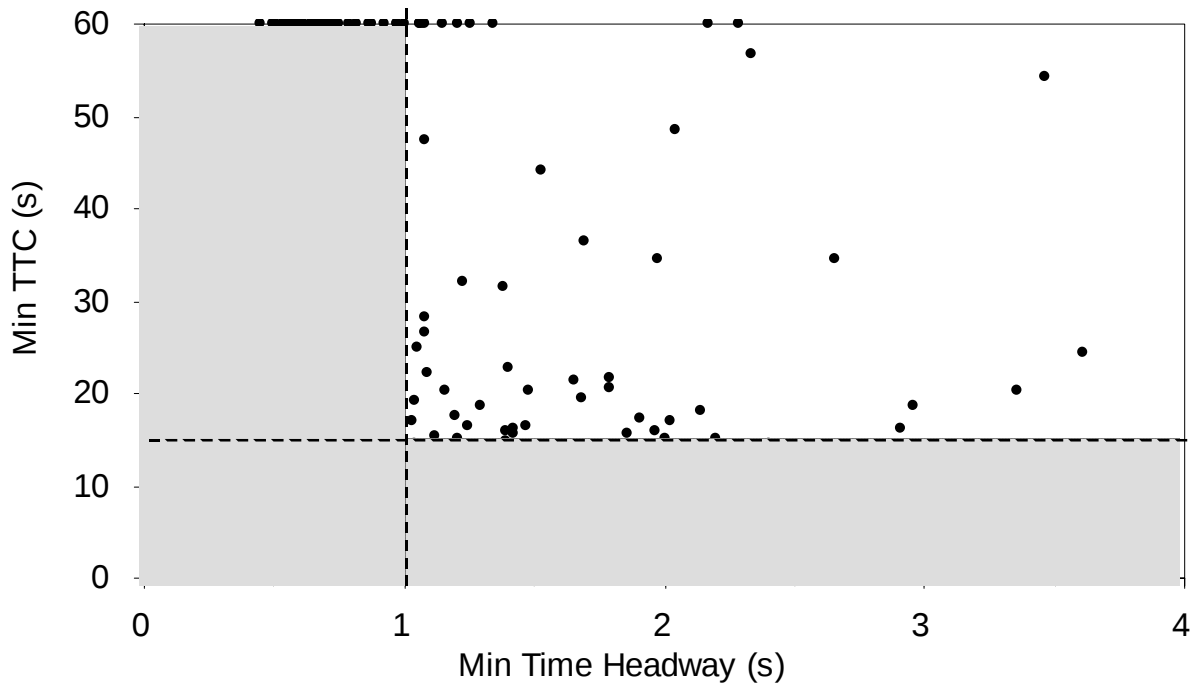


Figure 8.1. Minimum time-to-contact (s) as a function of minimum time-headway (s) during the 3-s prior to when the maneuvers were initiated for the slow lead vehicle lane changes to the left.

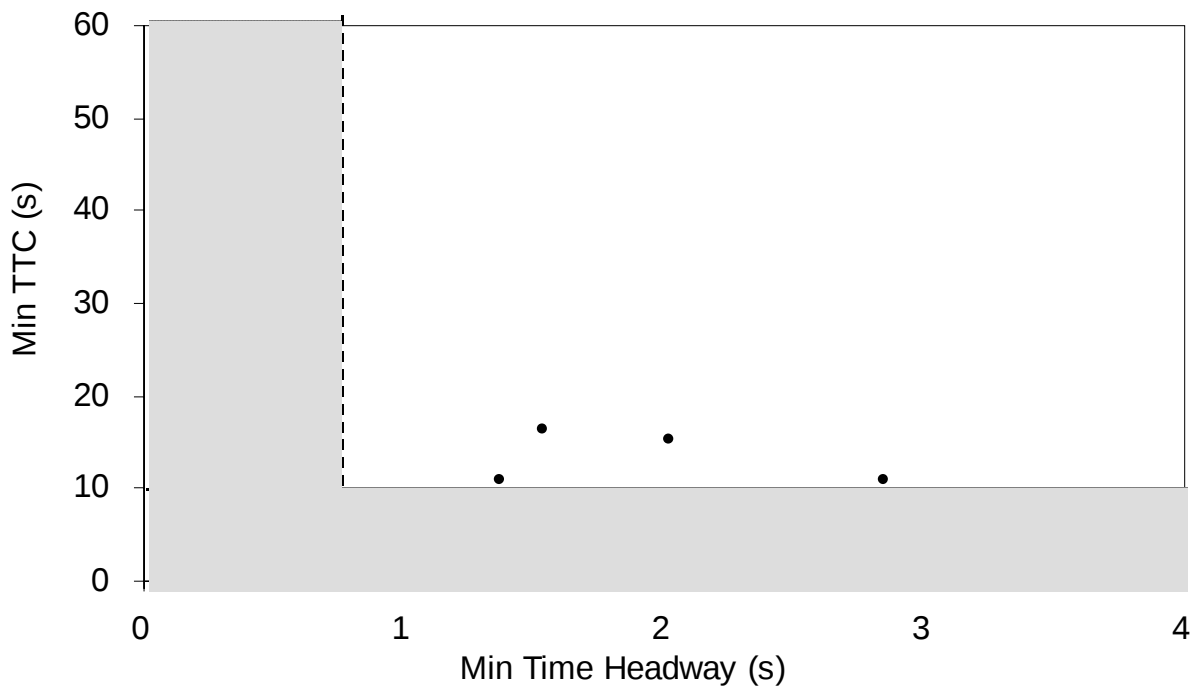


Figure 8.2. Minimum time-to-contact (s) as a function of minimum time-headway (s) during the 3-s prior to when the maneuvers were initiated for the slow lead vehicle lane changes to the right.

Figure 8.2 displays the minimum time-to-contact (s) as a function of minimum time-headway (s) during the 3-s prior to when the maneuvers were initiated for the slow lead vehicle lane changes to the right. The horizontal line represents a time-to-contact criterion of 10 s and the vertical line represents a time-headway criterion of 0.75 s. The combined area of these two criteria bound 86% of the 27 cases of left slow lead vehicle lane changes.

One important consideration of this analysis is that the sample of events that were analyzed are not representative of lane changes as a whole but instead the sample of 500 lane changes is skewed (by the VTTI researchers) toward those of higher severity and urgency ratings. However, the more urgent and severe lane changes are more likely to be important for adaptive systems. For example, it is only the more severe slow lead vehicle lane changes that would lead to FCW nuisance alerts. The nature of this sample is likely to be an important consideration for generalizing these data to other lane changes. For this reason, although the general strategy for deciding when to change lanes may be valid, the actual time-to-contact and time-headway values presented in this analysis should be treated with skepticism.

Another useful source of information for determining whether there exists a motive for changing lanes is to examine the radar data of vehicles in the destination lane also. For a slow lead vehicle to motivate a lane change, the destination lane must be preferable to the current lane. Therefore, the system should also analyze the time-to-contact and time-headway of the destination lane and assess whether the destination lane is likely to be preferable to the current lane.

Section 8.3.2 discussed how affordance information could be used to rule out whether a lane change is likely. In the case of lane changes motivated by a slow lead vehicle, the most pertinent information regarding the affordance of the lane change is whether a lane is present and whether the lane is immediately available. A GPS/map-matching system or a forward-looking vision system could provide information about whether the lane exists and a side-obstacle detection system could inform the system about whether a lane change is immediately possible.

Because turn signals are only used during 46 and 34 percent of left and right lane changes motivated by slow lead vehicles, a reliable intent-inference system must move beyond just using the turn signal. Task 8 (Intent) analyzed the first order Markov matrices for the left and right lane changes, containing the transitions between different glance locations. Table 8.4 tabulates the percentage of cases (out of the 265 slow lead vehicle left lane changes) in which the driver transitioned between the two glance locations at least once during the 3 s prior to the maneuver execution. This table demonstrates that glance transitions tend to be clustered within the light gray region and there are relatively few exceptions to this. For example, in 113 cases out of 265, drivers transition their focus from the center forward (CF) region to the rear view mirror (RVM). In 91 percent of the 265 cases, the driver transitioned between the regions highlighted in gray at least once during the 3 s prior to the execution of a slow lead vehicle lane change to the left. In 84 percent of the 265 cases, these transitions occurred at least twice or more.

Table 8.4. Percentage of Glance Location Transitions During the 3 s Before Execution of a Slow Lead Vehicle Lane Change to the Left

		Glances To						
		LBS	LW	LM	LF	CF	RVM	IC
Glances From	LBS							
	LW	9				12		
	LM	10	7			23		
	LF			7		13		
	CF		18	39	12		42	14
	RVM				7	39		
IC		16						

Note: The cells represent the percentage of cases (out of 267) in which the driver transitions glances from one location to the other at least once. Negligible values (where the numerator is zero or one or the percentage is less than 5) have been removed to provide focus to the table. The light gray region includes transitions from and to the center forward (CF), rear view mirror (RVM), left forward (LF), left mirror (LM), left window (LW), and left blind spot (LBS) regions and indicates transitions likely to be relevant to this maneuver.

Table 8.5. Percentage of Glance Location Transitions During the 3 s Before Execution of a Slow Lead Vehicle Lane Change to the Right

		Glances To				
		CF	RVM	RF	RM	RBS
Glances From	CF		52	11	11	11
	RVM	41			7	
	RF	15				
	RM	11				
	RBS	7				

Note: The cells represent the percentage of cases (out of 27) in which the driver transitions glances from one location to the other at least once. Negligible values (where the numerator is zero or one or the percentage is less than 5) have been removed to provide focus to the table. The light gray region includes transitions from and to the center forward (CF), rear view mirror (RVM), right forward (RF), right mirror (RM), and right blind spot (RBS) regions and indicates transitions likely to be relevant to this maneuver.

Table 8.5 tabulates the percentage of cases (out of the 27) in which the driver transitioned between the two glance locations at least once during the 3 s prior to the maneuver execution for the slow lead vehicle lane changes to the right. This table reveals that the majority of glance location transitions tend to occur between the center forward (CF) region and the rear view mirror (RVM) in both directions. In 81 percent of the 27 cases, the driver transitioned between the regions highlighted in light gray at least once during the 3 s prior to the execution of a slow lead vehicle lane changes to the right. In 63 percent of the 27 cases, these transitions occurred at least twice or more. Although this analysis is based on relatively few cases (27), it suggests that drivers rely quite heavily on the rear view mirror during lane changes to the right. The less frequent glances to and from the right mirror (RM), right blindspot (RBS), and right window (RW) are not surprising given that these glances require more effort and the driver is normally traveling faster than the traffic in the right hand lane, so is usually rely on glances to right forward (RF) and center forward (CF) regions to know when the right lane is available.

8.4.2 Preparation to Exit

The preparation to exit lane changes are motivated by the driver needing to move into the appropriate lane for an upcoming highway exit event. For example, if the exit lane is on the right, the host vehicle will need to make a right lane change if it is currently located in the left lane. Lane changes that are motivated by preparation to exit account for approximately 23 percent of the lane changes collected in the naturalistic lane change study.

In order for a system to detect that the preparation-to-exit motive exists, the system must determine that (1) there is an upcoming exit, (2) the host vehicle is likely to be taking this exit, and (3) the host vehicle is not yet in the exit lane. To determine that there is an upcoming exit, the most obvious method for solving this problem is to use a GPS/map-matching system. If such a system is not present, a forward-looking vision processor that is capable of detecting upcoming exits may be a possible alternative. To detect that the host vehicle is likely to use the upcoming exit, the system can either rely on previous history (e.g., the driver may traverse the same exit every day during a commute to work) or on route information if it is programmed into an available navigation system. Finally to detect that there is a disparity between the exit lane and the current lane that the host vehicle occupies, the system would require a system that knows which lane is associated with the upcoming exit (probably the same system that identified that an upcoming exit exists) and a forward-looking vision processor that can determine which lane the host vehicle currently occupies.

Like the slow lead vehicle lane changes, the most critical affordance is the existence and availability of a destination lane. Of the lane changes that are motivated by exit preparation, 68 and 46 percent are signaled with a turn signal for left and right lane changes respectively. Therefore there is likely to be sufficient room for improvement over an intent-inference system that solely relies on a turn signal. To examine additional pre-maneuver behaviors measures, Task 8 (Intent) analyzed the first order Markov matrices for the left and right lane changes, containing the transitions between different glance locations. Table 8.6 tabulates the percentage of cases (out of the 22 exit preparation left lane changes) in which the driver

transitioned between the two glance locations at least once during the 3 s prior to the maneuver execution. This table reveals that in this relatively small sample (22) glance transitions tend to be clustered within the light gray region. In all 22 cases, the driver transitioned between the regions highlighted in gray at least once during the 3 s prior to the execution of a slow lead vehicle lane change to the left. In 91 percent of the 22 cases, these transitions occurred at least twice or more.

Table 8.6. Percentage of Glance Location Transitions During the 3 s Before Execution of an Exit Preparation Lane Change to the Left

		Glances To						
		LBS	LW	LM	LF	CF	RVM	IC
Glances From	LBS							
	LW	9		9				
	LM		18		14	45		
	LF			9				
	CF	14	9	59	9		27	
	RVM					23		
	IC					14		

Note: The cells represent the percentage of cases (out of 22) in which the driver transitions glances from one location to the other at least once. Negligible values (where the numerator is zero or one or the percentage is less than 5) have been removed to provide focus to the table. The light gray region includes transitions from and to the center forward (CF), rear view mirror (RVM), left forward (LF), left mirror (LM), left window (LW), and left blind spot (LBS) regions and indicates transitions likely to be relevant to this maneuver.

Table 8.7 tabulates the percentage of cases (out of 50 exit preparation right lane changes) in which the driver transitioned between the two glance locations at least once during the 3 s prior to the maneuver execution. Again, the majority of glance transitions tend to occur between the locations highlighted in light gray. In 74 percent of the 50 cases, the driver transitioned between the regions highlighted in gray at least once during the 3 s prior to the execution of an exit preparation changes to the right. In 50 of the 50 cases, these transitions occurred at least twice or more.

Table 8.7. Percentage of Glance Location Transitions During the 3 s Before Execution of an Exit Preparation Lane Change to the Right

		Glances To							
		LF	IC	CF	RVM	RF	RM	RW	RBS
Glances From	LF			6					
	IC			8					
	CF	6	6		42	16	10		10
	RVM			28					
	RF			12			6		
	RM			10					
	RW								
	RBS								

Note: The cells represent the percentage of cases (out of 50) in which the driver transitions glances from one location to the other at least once. Negligible values (where the numerator is zero or one or the percentage is less than 5) have been removed to provide focus to the table. The light gray region includes transitions from and to the center forward (CF), rear view mirror (RVM), right forward (RF), right mirror (RM), right window, and right blind spot (RBS) regions and indicates transitions likely to be relevant to this maneuver.

8.4.3 Return to Original Lane: Right

The return to original lane changes to the right are motivated by the driver wanting to move back into the preferred lane after the maneuver in the left lane is complete. Because the left lane is generally considered to exist for the purpose of passing slower traffic, many drivers prefer to occupy the right lane by default and only use the left lane when a need to pass arises. Therefore rather than representing a motive per se, it instead represents a lack of motive to continue in the left lane. The return to right lane events account for approximately 17 percent of the lane changes collected in the naturalistic lane change study and comprise the second largest category of lane changes.

Because this type of lane change is a return to the right lane, by definition these lane changes must occur after a left lane change. Task 8 (Intent) analyzed the data set to investigate how much time occurred between the left lane change and the subsequent return to the right lane. Because 79 of the 265 slow lead vehicle left lane changes included return lane changes back into the right lane, this analysis was conducted on the slow lead vehicle lane changes with returns. Figure 8.3 displays the time intervals between the completion of the left lane change (slow lead vehicle event) and the initial execution of the return lane change to the right as a function of the percentile. The mean interval between changes was 1.78 s with a standard deviation of 0.97 s. The 95th percentile for these intervals is 3.43 s. This relatively short time interval between lane changes may suggest that a simple timer could be used to anticipate the motive to return to the right lane.

However, one limitation to this analysis is that the return lane changes that were analyzed may have been a biased sample that was more likely to include return lane changes if they occurred shortly after the initial lane change. As previously mentioned, the sample of 500 lane changes as a whole were also biased toward more urgent and severe lane changes. This is reflected in the relatively low mean value of 1.78 s, which suggests that the host vehicle was traveling significantly faster than the vehicle that was being passed on the right. However, note that host vehicle may have already gained significant ground on the lead vehicle prior to the completion of the left lane change.

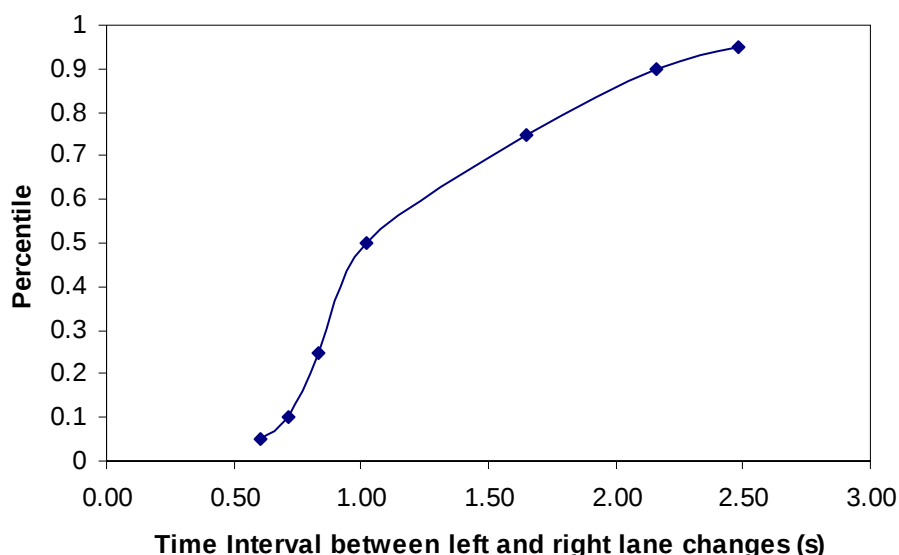


Figure 8.3. The Percentile of time intervals between the completion of the left lane change (slow lead vehicle event) and the initial execution of the return lane change to the right.

A more sophisticated strategy for detecting the motive to return to the right lane is to examine the traffic in the right lane. Beyond the immediate availability of the right lane that determines whether the lane change is possible (affordance), the proximity and rate of closure to the lead vehicles in the right lane may indicate whether the driver will perceive the lane change as being desirable. As discussed in Section 8.3.2 (Affordances), the affordance module could use either a blind-spot sensor or make projections based on the forward-looking sensor to predict whether the right lane is clear of traffic. Similar criteria as those used in the slow lead vehicle lane change category (e.g., if the lead vehicle in the right lane is too close or traveling more slowly) could also be extended to assess when it is likely that the driver may desire to return to the default lane.

Table 8.8 tabulates the percentage of cases (out of the 35 return lane changes) in which the driver transitioned between the two glance locations at least once during the 3 s prior to the maneuver execution. The majority of glance transitions tend to occur between the locations highlighted in light gray, however in this case more exceptions are evident, suggesting that the left forward (LF) and left mirror (LM) regions may provide useful information for some drivers. The most common glance transitions are those between the center forward (CF) and rear view mirror (RVM) regions. In 89 percent of the 35 cases, the driver transitioned between the regions highlighted in gray at least once during the 3 s prior to the execution of

the return lane changes to the right. In 63 percent of the 35 cases, these transitions occurred at least twice or more.

Table 8.8. Percentage of Glance Location Transitions During the 3 s Before Execution of a Return Lane Change to the Right

		Glances To								
		O	LM	LF	IC	CF	RVM	RF	RM	RW
Glances From	O									
	LM					6				
	LF					14				
	IC					9				
	CF	6		11	6		69	14	9	6
	RVM					40			14	
	RF					11				
	RM									
	RW					9				

Note: The cells represent the percentage of cases (out of 35) in which the driver transitions glances from one location to the other at least once. Negligible values (where the numerator is zero or one or the percentage is less than 5) have been removed to provide focus to the table. The light gray region includes transitions from and to the center forward (CF), rear view mirror (RVM), right forward (RF), right mirror (RM), right window, and right blind spot (RBS) regions and indicates transitions likely to be relevant to this maneuver.

8.4.4 Tailgating Rear Vehicle: Right

The tailgating rear vehicle lane changes to the right are motivated by a vehicle behind the host vehicle applying pressure to change lanes by tailgating the host vehicle. These events account for approximately 4 percent of the lane changes collected in the naturalistic lane change study. As mentioned in Section 8.3.1, it may be possible to detect a tailgating lead vehicle with a rear-looking detection system when the tailgating is extreme. Delphi's back-up aid radar is capable of looking back 5 m, which could theoretically detect a vehicle that is tailgating at a time-headway of 0.25 s when both vehicles are traveling at 45 mph. The other major indicator of motive is that the host vehicle is in the left lane, which could potentially be detected by a forward-looking vision processor. Like the other types of lane changes that have been discussed in this section, the most relevant affordance is the existence and availability of the destination (right) lane.

Table 8.9 tabulates the percentage of tailgating rear vehicle changes in which the driver transitioned between the two glance locations at least once during the 3 s prior to the maneuver execution. Unfortunately, there were only 15 cases of these lane changes and so this table is not as informative as the others in this section. Not surprisingly, the driver

transitions glances frequently to and from the rear view mirror. In 80 percent of the 15 cases, the driver transitioned specifically from the center forward region (CF) to the rear view mirror (RVM) region. Glances other than those between these two regions were relatively rare. In Section 8.3.3, Table 8.3 also indicated that in all cases, drivers spent time glancing at both the center forward (CF) region and the rear view mirror (RVM) region. On average, drivers spent almost one second of the three seconds prior to the maneuver glancing at the rear view mirror (RVM) region.

Table 8.9. Percentage of Glance Location Transitions During the 3 s Before Execution of a Tailgating Rear Vehicle Lane Change to the Right

		Glances To						
		LF	CF	RVM	RF	RM	RW	RBS
Glances From	LF							
	CF	13		80	13			
	RVM		53					
	RF							
	RM							
	RW							
	RBS							

Note: The cells represent the percentage of cases (out of 15) in which the driver transitions glances from one location to the other at least once. Negligible values (where the numerator is zero or one or the percentage is less than 5) have been removed to provide focus to the table. The light gray region includes transitions from and to the center forward (CF), rear view mirror (RVM), right forward (RF), right mirror (RM), right window, and right blind spot (RBS) regions and indicates transitions likely to be relevant to this maneuver.

8.4.5 Other Lane Changes

There are three types of lane change motives that appeared in Table 8.2 that were not analyzed in depth for Task 8 (Intent). Those motives included enter highway (left and right), merging lead vehicle (left), and lane drop (left and right). These types of lane changes account for a combined total of 12 percent of the 8667 lane changes that were observed in the VTTI study, however, there was insufficient data in the in-depth data set for a reasonable analysis. There were 23 and 6 samples of the left and right enter highway lane changes respectively, 17 samples of the merging lead vehicle lane changes, and 9 and 6 samples of the left and right lane drop lane changes respectively.

The other reason for excluding these cases from the Task 8 (Intent) analysis is that these types of lane changes are likely to be best predicted based on information other than glance

location patterns. For example, because the data revealed that drivers use the turn signal 94 percent of the time when making a “merging lead vehicle lane change” to the left, an intent algorithm need not examine any other source of information for predicting these lane changes. It is unlikely that an intent algorithm could improve upon such a reliable indicator. Both the enter highway and lane drop lane changes are likely to be best predicted by examining the environment rather than examining the driver. If a GPS/map-matching or forward-looking vision processor system reveals that the lane that the host vehicle is currently occupying will soon cease to exist, the probability that the driver will make a lane change is near 1. Likewise, the highway entry situation represents a special case of a lane drop lane change when the entry lane will soon cease to exist. The unifying feature of these lane changes is that it is most likely that they can be predicted by focusing on a single source of information (the turn signal for merging lead vehicle changes and the lane characteristics for highway entry and lane drop lane changes) rather than on a fusion of different sources of information.

8.5 CONCLUSIONS

The VTTI naturalistic lane change study was extremely informative about the nature of lane changes. The categorization of different types of motives for changing lanes not only influenced the specific analyses for diagnostic measures but also contributed to the overall framework for detecting driver intent. A framework that focuses on motive, affordances, and pre-maneuver behaviors provides a way of fusing together both external/environmental information and internal/driver information for predicting a specific maneuver. It is likely that this framework may be generalized beyond lane changes and may help frame the problem for predicting other types of maneuvers also (e.g., turns, braking, or avoidance maneuvers).

The naturalistic lane change data set was the only data set that was available that afforded an in-depth intent analysis of driver intent (it provided eye-gaze locations 3 s prior to the maneuver). Hypotheses were generated for discriminating lane-change intents from non-lane-change events. Simple comparisons between Lee et al.'s (2004) lane change data set and the null data sets of Mourant and Donahue (1974) and Carter and Laya (1998) suggest that a driver's glance behavior tends to show specific patterns prior to lane changes. Although it is difficult to assess at this stage, fusing data from the three modules: motive, affordance, and pre-maneuver behaviors may increase the probability of accurately inferring driver intention. Despite the driving-simulator work of Salvucci and colleagues, the kinematic (e.g., yaw-rate) and control (throttle position) variables did not appear to be indicative of driver intentions before the maneuvers were executed or even of the maneuver once it had begun.

As useful as the naturalistic lane change data set clearly was, it only provided cases that preceded lane changes but did not include a set of null cases (where no lane change occurred). Therefore, it could only be concluded that there are certain circumstances that appear to reliably coincide with lane changes. The rate at which these circumstances occur when no lane change takes place could not yet be evaluated. To examine the distribution of intent false alarms a set of null cases is required. If such a data set were available, it would afford a more sophisticated examination of intent-inference that could investigate both types of errors (false positives and false negatives) and successes (true positives and true negatives). Using the signal detection framework, this analysis could examine the precision of the detection algorithm (d') and the bias of the criteria toward one type of error over another (β). If an intent-inference system is used to suppress safety warning systems, false positives in this system would lead to false negatives in the safety warning systems (warnings when the driver actually needs them). For this reason, the intent-inference system should consider adopting a bias (β) that produces more false negatives than false positives. Bayes theorem is also likely to provide a useful way of measuring the reliability of the intent-inference system, by providing a framework for evaluating the probabilities of a specific maneuver, given the observed data pattern.

8.5.1 Human Factors Guidelines

Clearly it is too early to make a useful set of human factors guidelines or recommendations. However, the VTTI data do suggest that the intent-inference problem may be approached using the modular framework that was described in Section 8.3 (Intent Detection Framework) that examines motive, affordances, and pre-maneuver behaviors. Furthermore, these data suggest that most types of lane changes will not be able to be reliably detected with a turn signal alone or based upon kinematics (e.g., yaw-rate) and control (throttle position) sources of data. Instead, it appears that glance locations may provide a useful source of information that can be fused with other sources of information (e.g., road geometry or radar data) to provide the basis for predicting lane changes.

8.5.2 Phase II planning

New naturalistic driving data must be collected that includes eye-tracking coordinates for both lane-change and non-lane-change events. A time window that extends back longer than 3 s may also afford more accurate prediction of driver intent. To achieve these requirements, Delphi plans to instrument a vehicle with the necessary sensor suite (including an eye-tracking system) and distribute it among Delphi commuters with medium to long range commutes (e.g., greater than 15 min). To facilitate this data collection, Delphi will train these drivers to activate the instrumentation and collect naturalistic data on their commutes. During these commutes, data will be recorded that may be divided into sets of lane change, turn, and null (no lane change or turn) events. Task 8 (Intent) will then use this naturalistic data set to develop and iteratively tune algorithms with the goal of reliably detecting intentions with minimal false alarms. This naturalistic data set could also be used for post-hoc algorithm development (running new algorithms on previously recorded data) for many other SAVE-IT tasks.

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