SAVE-IT

SAfety VEhicles using adaptive Interface Technology (Task 8): A Literature Review of 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.

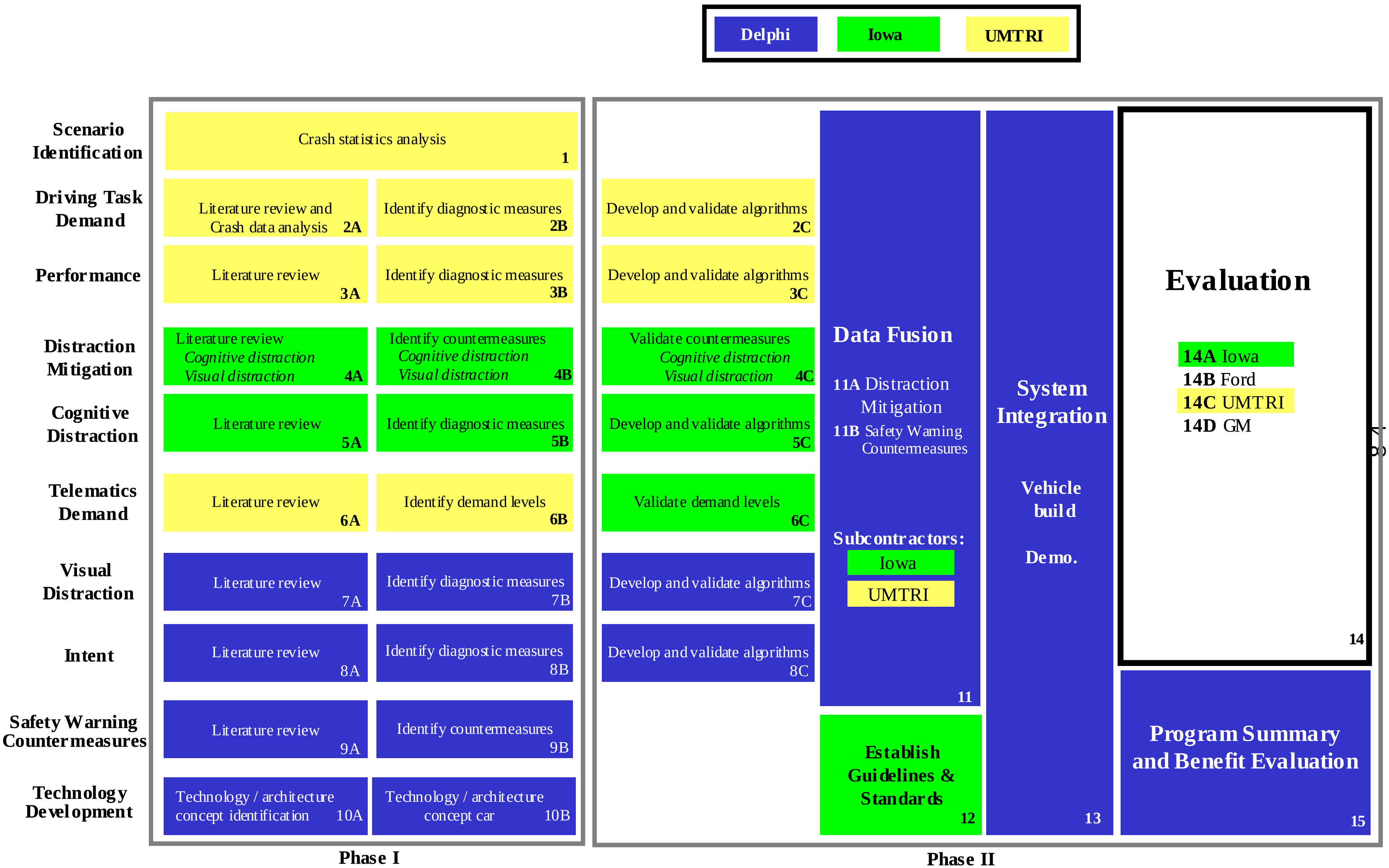

Figure i: SAVE-IT tasks

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 tasks[1]. 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.

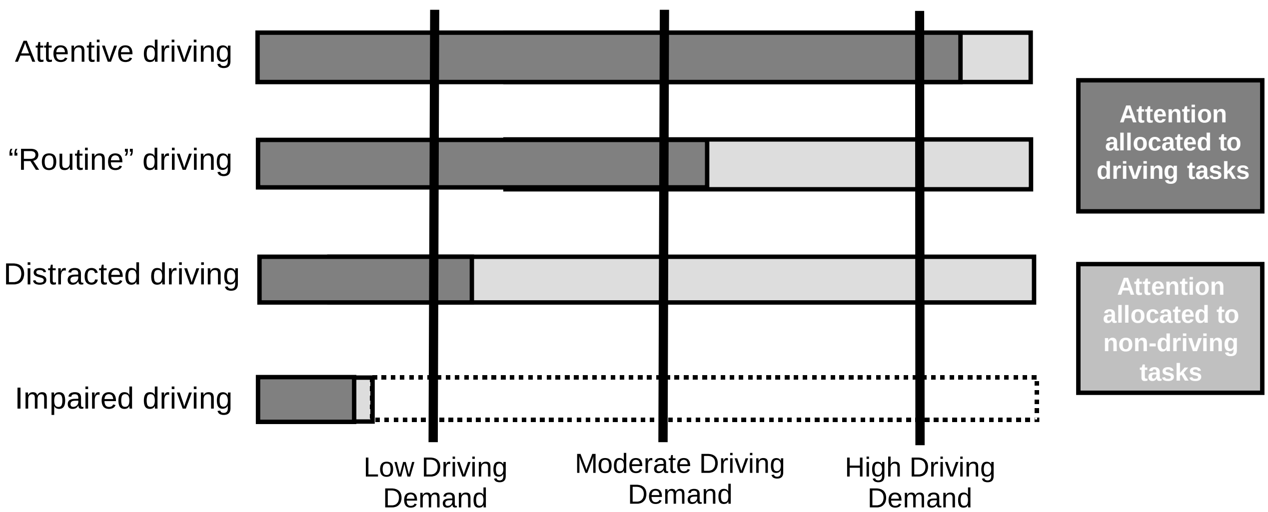

Figure ii. Attention allocation to driving and non-driving tasks

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 literature review report that documents the research progress to date (March 1--September 10, 2003) in Phase I. During the period of March-September 2003, the effort has been focused on the first Phase I sub-task: Literature Review. In this report, previous experiments are discussed, research findings are reported, and research needs are identified. This literature review report also serves to establish the research strategies of each task.

8.1 INTRODUCTION

Task 8 (Intent) supports the needs of the SAVE-IT program by examining methods that allow the inference of driver intentions. This information could potentially benefit both the distraction mitigation and safety warning countermeasures sub-systems. For example, if a system can infer an intention to pass, the system might screen phone calls while the driver executes the maneuver, negating the source of distraction during a perceptually demanding task. The output of this task could also be connected to the safety warning countermeasures. Intent inference has the potential to reduce the frequency of nuisance alerts. For example, LeBlanc, Bareket, Ervin, and Fancher (2002) revealed that nuisance alerts are common during lane-transitions. There are several scenarios of lane-transition that can lead to nuisance alerts for the Forward Collision Warning (FCW) system, including approaching to pass, host vehicle turning or changing lanes, or lead vehicle turning or changing lanes (LeBlanc et al., 2002). A system that can reliably identify intents to pass, change lanes, or turn could suppress alerts that precede the predicted maneuver. Billings (1997) stressed how important the communication of intent is between human and machine for effective communication and the reduction of false alarms.

Inferring the driver's immediate intention provides the system with additional capacity to be adaptive to the driver. In a review of the human factors work conducted in the European Union, Hoedemaker, de Riddler, and Janssen (2002) defined an adaptive interface as:

> *A system that in some way takes into account the momentary state of the driver, in particular his present level of workload, in determining the appropriate timing and the content of the supporting message or intervening activity the system will produce.* (p. 7)

Although the measurement of workload or distraction is one obvious way for a system to be adaptive, there are several other manners in which a system can adapt. Piersma (1993) listed the following sources of information to which a system can adapt:

- Driver Preferences
- Secondary tasks
- Current driver workload
- Traffic situation
- Driving tasks currently performed
- Individual driving history

Of particular interest for Task 8, is the adaptation "to driving tasks currently performed". Piersma's specific example included not providing navigation information while the driver is passing another vehicle. In terms of the SAVE-IT program, this would be an example of Distraction Mitigation (Task 4) as a function of Intent (Task 8). As the availability of vehicular sensors increases (especially eye-tracking), inferring intent becomes increasingly feasible. In the last decade, many researchers in the automotive arena have referred to the potential of intent-inference systems to improve system performance, (e.g., Pomerleau, Jochem, Thorpe, Batavia, Pape, McMillan, Brown, and Everson, 1999; Tijerina, 1999; Tijerina and Hetrick, 1997; Geiser and Nirshcl, 1993; Mazzae and Garrott, 1995; NHTSA Benefits Working Group, 1996; Chovan, Tijerina, Alexander, Hendricks, 1994; Young, Eberhard, and Moffa, 1995; Brunson, Kyle, Phamdo, and Preziotti, 2002; Lee, Olsen, and Wierwille, 2002). Although the reality of real-time intent inference is relatively new to the automotive domain, some researchers have begun to examine methods for detecting intent (e.g., Goldman, Miller, Harp, and Plochner, 1995; Liu, 1999; Salvucci, 2004; Salvucci, and Liu, 2002; Takahashi, 2000; Yuhara and Tajima, 2001). This document will review and discuss the literature that pertains to the inference of driver intention.

8.1.1 Defining Intent

Intent is defined in Merriam Webster's dictionary as "the act or fact of intending" and intention is defined as "a determination to act in a certain way". Much of the focus of intent in psychology has been in the domain of Ecological Psychology. Rather than focusing on how people respond to relatively simple laboratory stimuli, Gibson framed the problems of psychology as the study of behavior in the context of the actor's intentions and environment. Gibson (1979/1986) coined 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 inference, 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. Therefore, an analysis of the environment has the potential to provide useful information for identifying driver intentions. Framed in terms of Ecological Psychology, driving behavior is constrained by the interactions between affordances, effectivities (potential range of possible behaviors of the driver-vehicle system), and the intentions of the driver.

The intentional constraints can be understood in a hierarchy, ranging from the abstract (e.g., to travel to the destination within a certain time interval) to concrete (e.g., keep the vehicle within the given lane), with more concrete intentions nested within more abstract intentions (Rasmussen, 1986). Even the more abstract goals, such as traveling to the destination, can be understood in the context of more abstract goals, such as earning wages if the destination is work. However, this task will focus on the intentions at the lower levels, which occur during shorter time intervals and are manifest in overt driving behaviors, such as changing lanes. For the purposes of Task 8, intent will be defined as:

A driver's determination to perform a specific driving maneuver (e.g., change lanes) in the immediate future (e.g., 3 to 5 s).

The goal of this task is to:

Identify a list of intents that are potentially useful for the distraction mitigation and safety warning countermeasures, and derive algorithms that can reliably infer these intentions before the intended maneuver is executed.

In this task, intent-inference refers to an algorithm inferring that a driver intends to make a lane change prior to the point at which that maneuver is executed. This can be contrasted with a maneuver-detection algorithm that detects a given maneuver while the maneuver is being executed. In the case of lane changes, whereas the latter task (maneuver-detection) could potentially be accomplished by a vision-based lane-tracking system, the former task (intent-inference) is more challenging, and is likely to require the fusion of several types of variables. The goal of Task 8 is that of intent-inference rather than maneuver-detection.

8.1.2 Overview of Task 8 (Intent) Literature Review

This document is organized into four sections, including this introduction section (Section 8.1). The next section (Section 8.2: Applications of Intent Inference) will describe the adaptive systems that will benefit from intent inference. Section 8.2 will discuss distraction mitigation systems and describe how these systems could benefit from intent inference. The benefits of intent inference will also be discussed for various safety warning countermeasures. Based on the discussion of safety warning countermeasures and distraction mitigation systems, Section 8.2 will conclude with a target list of intents. The next section (8.3: Intent Inference) will review the literature for potential information to support the inference of intent, including the lane change literature, eye-movement literature and a small set of studies that attempt to detect driver intentions. The final section (8.4: Hypotheses for Intent Inference) will propose hypotheses for how the SAVE-IT systems may detect the targeted intents. Section 8.4 will conclude with a research strategy for Task 8.

8.2 APPLICATIONS OF INTENT INFERENCE

The need for intent inference is derived from the two SAVE-IT subsystems: distraction mitigation and safety warning countermeasures. In the distraction mitigation task, knowledge of driver intent can be used to suppress unnecessary non-driving task activity before and during highly demanding driving maneuvers. For example, passing on a two-lane rural road often requires the driver's full attention and could be an inopportune moment for a cell phone call. Safety warning countermeasures present the difficult problem of nuisance alerts (providing alerts to the driver when no alert is warranted). Because of the complexity of the driving environment, it is virtually impossible to prevent all nuisance alerts. Many nuisance alerts occur in forward collision warning systems during lane-transitions (LeBlanc et. al., 2002). Suppressing these alerts during certain driving maneuvers may potentially reduce a large percentage of nuisance alerts, which could improve driver acceptance of the system. In the context of the European PROMETHEUS program, Geiser and Nirshcl (1993) proposed that the Driver Warning System (DWS) should detect intent information for suppressing premature warnings. Similarly, in the United States the NHTSA Benefits Working Group (1996) recommended that:

> *A CAS should be intelligent enough to discern driver's intent (e.g., intent to change lanes, lane change start) though this is difficult to do. If available, such indicators might selectively alter the drive alerts or warning (e.g., thresholds, presentation mode, stimulus magnitude, etc.) (p. 1-9)*

8.2.1 Distraction Mitigation

The goal of the distraction mitigation subsystem is to monitor the attention allocation of the driver and the driving task demand in order to warn the driver or adapt the non-driving task demand levels to support sufficient allocation of attention. A driver's intention to engage in a passing or turning maneuver has obvious consequences for distraction mitigation. If a driver's intention to turn, pass, or maneuver to avoid is detected, the instantaneous level of driving task demand is likely to be greater than when a driver is merely engaged in typical lane-keeping behavior. Such a deviation from the behaviors of normal lane keeping is likely to require a completely different analysis of attention allocation.

It is likely that under most circumstances when a driver is intending to engage in a maneuver in the immediate future, that driver must be relatively attentive to the general driving task. To reduce nuisance alerts, the distraction mitigation system might suppress distraction-related warnings while a driver is intending to engage in the maneuver. A warning that occurs just prior to or during a maneuver is likely to be distracting to the driver. The other function of the distraction mitigation system is to adapt the level of non-driving task demand that is available to the driver. Because engaging in maneuvers is likely to demand greater levels of attention, the distraction mitigation system could potentially benefit the driver by suppressing low priority messages and incoming phone calls. For example, a low fuel warning could probably be delayed until after the maneuver is completed. Thus far, most of the attentional-demand literature has focused on non-driving task demand rather than on driving maneuvers, so it is difficult to precisely determine which driving maneuvers are the most demanding. Subjective experience suggests that the following list may represent many of the greater-demand driving maneuvers:

- Steering to avoid an obstacle
- Braking to avoid an obstacle
- Passing
- Turning
- Merging
- Changing Lanes

Passing, turning, merging, and possibly maneuvering to avoid an obstacle may represent special cases of lane changes. The only intent that is not necessarily tied to a lane deviation is the intent to brake.

8.2.2 Safety Warning Countermeasures

A major challenge for safety warning countermeasures is to provide sufficient warning to drivers in order to prevent collision with a tolerable rate of nuisance alerts. Nuisance alerts not only decrease driver acceptance of the system, but could also undermine the effectiveness of the alert, by reducing the credibility of the system (Lerner, Dekker, Steinberg and Huey, 1996a; Lee, McGehee, Brown, & Raby, 1999, Horowitz and Dingus, 1992).

Perhaps the most useful application of intent-inference is to reduce the occurrences of nuisance alerts that result from Lane Drift Warning (LDW) systems. Pomerleau et al. (1999) proposed LDW systems as a strategy for reducing run-off-road collisions. LDW systems monitor the driver's lane keeping performance (usually with image processing of a forward camera) and warn if the host vehicle is beginning to drift out of the lane. Because lane-keeping behavior varies so greatly across individuals and across driving situations and environments (Pomerleau et al., 1999), nuisance alerts are likely to occur quite frequently. Pomerleau et al. observed that lane-keeping behavior varies greatly as a function of lane-width, with tighter performance for narrower lanes. When fewer negative consequences are present for imprecise lane keeping, drivers are less likely to expend the additional effort required to track the lane precisely. Pomerleau et al. estimated that for 59 percent warning coverage, nuisance alerts were likely to occur at a rate of 2 alerts per hour for passenger cars, with 4-ft of maneuvering room on both sides of the lane. The nuisance alert rate is expected to far exceed the rate of appropriate alerts, because Pomerleau et al. estimated that road departure occurs on average once every 84 years of a driver's life. In response to the estimated frequency of nuisance alerts, Pomerleau et al. recommended:

A LDWS should attempt to determine driver intentions in order to minimize nuisance alarms. It should attempt to avoid issuing warnings for intentional lane excursions which can result when performing a lane change, driving onto the shoulder to avoid obstacles in the travel lane, or stopping beside the road for a vehicle or passenger emergency. (p. 22)

Pomerleau et al. suggested that driver intent might potentially be detected by a system that monitors brake and turn signals, the vehicle position relative to the lane markings, and the presence of any sudden steering input that might indicate a sudden evasive maneuver. They proposed that intentional lane deviation could potentially be discriminated from unintentional lane deviation, possibly by the existence of a sudden steering input versus a slow and steady motion away from the center of the lane. In addition to the overt driver behaviors, they also suggested monitoring the affordances of the environment, such as consulting the digital map for the existence of exit ramps or cross streets (i.e., places where a driver might direct an intentional maneuver) or monitoring other collision warning systems (e.g., FCW) for evidence that the driver may be executing an intentional avoidance maneuver.

Although it did not involve a warning system, Yuhara and Tajima's (2001) work with an adaptive steering system may also be relevant. Yuhara and Tajima adjusted the steering system gain as a function of the driver's mood and recognized intention. The weights for the weighted sum of vehicle's lateral position and yaw angle could be adaptively varied depending on whether the driver was intending to maintain lane position or change lanes. To detect lane changes, they used an auto-regressive moving average model with a high-pass filter on the steering-wheel angle. Because the inference algorithm used only steering-wheel angle, lane changes could only be detected when the lane change maneuver was already initiated and is therefore perhaps more of a lane-detection algorithm than an intent-inference algorithm per se. Although Yuhara and Tajima discovered that the system appeared to reduce subjective workload, the system might potentially be enhanced further by earlier inference of intent to change lanes.

Although LDW is the most obvious application of driver intent, other warning systems could also benefit from driver intent information. Other examples of warning systems that the SAVE-IT program may address include Forward Collision Warning (FCW) and blind-spot warning (BSW), which may also be greatly enhanced with intent information.

There are several types of FCW nuisance alerts. Table 8.1 below presents the classification system used by Kiefer et al. (1999) to describe different types of alert scenarios for a FCW system, based on the true state of the world and whether the alert occurred. The three types of nuisance alerts are

- false alerts, where no obstacle was present (usually generated from system noise)
- in-path nuisance alerts, where an obstacle is in path however the situation does not represent a legitimate threat (e.g., the lead vehicle is about to turn or change lanes, or the algorithm criterion is set too cautiously), and

- out-of-path nuisance alerts, where the obstacle is outside the path that the host vehicle is about to travel (e.g., a parked car or sign on the side of the street).

Table 8.1. Kiefer et al.'s (1999) classification of different alert occurrences.

	No Obstacle	In-path vehicle		Out-of-path objects
		Alarming situation	Non-alarming situation	
Alert occurred	*False alert*	*Appropriate alert*	*In-path nuisance alert*	*Out-of-path nuisance alert*
No alert occurred	*Appropriate non-alert*	*Missed alert*	*Appropriate non-alert*	*Appropriate non-alert*

Although false alerts are likely to be relatively rare with current technologies, many circumstances can contribute to in-path and out-of-path nuisance alerts. Kiefer et al. list examples of the source of out-of-path nuisance alerts, including overhead objects, road surface and debris, adjacent lanes of traffic, and roadside clutter (e.g., curved road guardrail, sign or pole, or parked vehicles). Unlike false alerts and out-of-path alerts, in-path nuisance alerts are largely a subjective phenomenon. A more aggressive driver might view an alert as inappropriate that a conservative driver perceives as appropriately timed.

Many nuisance alerts occur during driving maneuvers, such as when a driver intends to pass a lead vehicle or to turn. In order to help guide the list of intents that the intent task will attempt to detect, this section will review some of the work that classifies different sources of Forward Collision Warning (FCW) nuisance alerts.

LeBlanc et al. (2002) analyzed the performance of two prototype FCW systems, system A, which responded only to moveable objects and included ACC functionality, and system B, which responded to both stationary and moveable objects. The researchers of this study drove the same 80-mi route, seven experiencing system A and six experienced system B. After the drive, these drivers were asked to indicate the percentage of alerts that were "useful", a "nuisance", or "missing/late". Many drivers interpreted "useful" as meaning "useful if the driver had been inattentive" and not necessarily "useful for an attentive driver". Analyses indicated that 21.1 percent of alerts were considered "useful", 66.4 percent were considered a "nuisance", 6 percent were considered "missing/late", and 5.4 percent were "other". Alerts were inhibited during driver braking, and this occurred on average for approximately 72 percent of potential alerting situations. During the total 378 miles of driving System B (responding to stationary objects) produced 122 alert activations, at a rate of 32 alerts/100 mi. Analyzing the alert activations, LeBlanc et al. broke the FCW alert activations into four different categories. These different types of activations are presented in Table 8.2.

LeBlanc et al. suggested that the scenarios of tailgating (5 percent), approaching to pass (14 percent), approaching a turning vehicle (19 percent), and two-lane pass by host (1 percent) represent situations wherein the driver was an actor in the conflict who intended or tolerated the risk. In these events (accounting for a total of 39 percent of the total) it is likely that the driver is relatively attentive and somewhat aware of the level of risk. Therefore providing an alert in these circumstances would likely be perceived as a nuisance. They argued that:

In most such cases, the driver clearly intends to cultivate or at least tolerates the conflict as an "appraised risk" within an otherwise deliberate driving tactic.

Table 8.2. LeBlanc et al.'s (2002) breakdown of nuisance alert categories

Relevant Scenarios	% Alerts
I. Host and Moving Target Traveling in Same Lane throughout Alert Episode	**23**
Approach to stopped vehicle	1
Approach to follow	7
Lead vehicle braking	10
Tailgating	5
II. Host and Moving Target Travel in Different Lanes Sometime During Alert Episode	**38**
Approach to pass	14
Approach to turning vehicle	19
Target gone, lead vehicle turning	3
Two-lane pass by host	1
Crossing path vehicle	1
III. Alert Triggered by Roadside Object	**32**
IV. Alert Trigger: Unknown or Errors	**7**

Preliminary data are also available from Ervin et al.'s (2003) analysis of the ACAS FOT pilot studies. In the Stage 2 pilot testing, in the 1390 miles of road traveled with the FCW system enabled, 92 alerts were presented to the driver at a rate of 6.6 alerts/100 mi. Of the 92 alerts, stationary targets accounted for almost half (42). Of the 50 moveable target alerts, 30 occurred during lead or host lane transitions, leaving 20 in-lane alert incidents. Mirroring LeBlanc et al.'s results, the largest contribution to in-lane incidents was lead vehicle deceleration (8.7 percent of alerts), followed by the host vehicle approaching the lead vehicle at a higher speed (7.6 percent), the host vehicle tailgating (5.4 percent) and the host vehicle accelerating (1.1 percent). The vast majority of lane-transition incidents involved the host vehicle approaching a turning lead vehicle (19.6 percent), followed by the host vehicle approaching a lead vehicle that is changing lanes (4.3 percent), the host vehicle approaching with the intent to pass (3.3 percent), the host or lead vehicle cutting in (3.3 percent), and the host vehicle approaching with the intent to move into a turning lane (2.2 percent).

Many nuisance alerts occur during lane-transitions, when the lead or host vehicle changes lanes. One example of this is when the driver of the host vehicle intends to overtake the lead vehicle and approaches the lead vehicle rapidly before initiating the lane change. During the rapid approach, the algorithm may calculate that there is sufficient threat to warrant some level of alert. Although many of the nuisance alerts occur before the host vehicle completes a pass or lane change (17 percent), the majority (73 percent) of the 30 lane-transition nuisance alerts in the ACAS FOT Stage-2 pilot testing were caused by the lead vehicle turning or changing lanes (Ervin et al., 2003). Unfortunately, the intent-inference algorithms of this task will only be able to focus on the intention of the driver of the host vehicle, and therefore they will not be able to provide a means of suppressing these types of alerts. The remaining 10 percent were attributed to either the lead or host vehicle “cutting-in”.

Brunson et al. (2002) used host vehicle acceleration in an attempt to detect the intent of the host driver vehicle passing for an FCW system. The rationale for this logic was that in many passing situations, the host vehicle will accelerate before passing the lead vehicle. Brunson et al. admitted that it would fail to capture the passing situations in which the host vehicle approaches the lead vehicle at a constant higher speed. When a turning or passing maneuver begins, it is likely that the driver is attentive. They used host vehicle acceleration as a trigger for suppressing FCW alerts, arguing that nuisance alerts during passing are “under the driver’s control.” They expressed the importance of detecting intent for FCW algorithms:

> *While the current algorithm uses acceleration, a significant change in the accelerator position may be a better indicator because it more directly reflects driver’s intent. No detection scheme has been implemented for the latter case because the host driver’s attentiveness cannot be inferred. Identifying a lane change maneuver via a vision system interpretation of road markings or an identifiable steering maneuver could eliminate some nuisance alerts of this type. (p. 4-5)*

The inference of intent may also potentially enhance Blind-spot Warning (BSW) systems. BSW systems monitor the lane immediately adjacent to the host vehicle and notify the driver of the presence of a vehicle in the blind spot. One of the difficulties with BSW systems is that vehicles are frequently present in the blind spot and frequently vehicles pass in and out of the blind spot. A system that warns the driver with a salient stimulus every time a vehicle is present in the blind spot is likely to be overly annoying to the driver. Several researchers have suggested designing the system so that it only provides an audio warning when a vehicle is in the blind spot and the turn signal is activated in the corresponding direction (Tijerina and Hetrick, 1997; Mazzae and Garrot, 1995; Chovan et al., 1994; Young et al., 1995). For the BSW system, the turn signal is used as evidence of an intention to change lanes. It is appropriate to warn a driver who is intending to travel into a lane that is currently occupied by another vehicle. Although the activation of a turn signal almost always indicates an intention to change lanes (or turn), many drivers infrequently use their turn signals before a maneuver (Tijerina and Hetrick, 1997; Mazzae and Garrot, 1995; Chovan et al., 1994; Young et al., 1995; Lee et al., 2002). Whereas turn signal-activation may indicate an intention to change lanes, the absence of turn-signal activation does not eliminate the possibility of an intent to change lanes. A more comprehensive method of intent inference is likely to enhance BSW systems.

BSW systems should not only provide warnings when a driver intends to change into an occupied lane of traffic, but also when a driver who does not intend to change lanes is changing lanes. The NHTSA Benefits Working Group (1996) estimated that 17 percent of lane change/merge accidents involve lane changes that were unintentional, many of which are likely to be caused by driver distraction. Because intentional and unintentional lane changes involve differing levels of driver attention, a system that can determine driver intent during a lane change, might warn a driver differently in the two circumstances.

8.2.3 List of Intents for Task 8 (Intent)

The motive for intent inference comes from the two major SAVE-IT subsystems: distraction mitigation and safety warning countermeasures. Sections 8.2.1 and 8.2.2 described how these systems could potentially use information regarding driver intent. In most cases, driver intent would be used as a trigger for suppressing some kind of warning or information presentation, but in the case of blind spot warning (BSW), driver intent to change lanes could actually be used to elevate the alert status. Table 8.3 presents a list of driver intents and presents their potential applications.

Although a driver's approach to a turning lead vehicle has the potential to lead to many nuisance alerts (Leblanc et al., 2002; Ervin et al. 2003), it does not represent a clear intention to maneuver like the other intentions in Table 8.3. The lead vehicle carries out more of the maneuvering than the host vehicle, and frequently the driver of the host vehicle does not take any overt action. Rather than targeting these nuisance alerts with intent inference, measuring the attention allocation of the driver may better target nuisance alerts of this type. When a driver is attentive to the lead vehicle and the lead vehicle azimuth is changing rapidly, the FCW system could suppress alerts.

Table 8.3. Potential SAVE-IT applications for driver intent categories

	Distraction Mitigation	**Safety Warning Countermeasures**		
Intent to:		**FCW**	**LDW**	**BSW**
Steering to avoid an obstacle	NAS, NDT	NAS	NAS	ALC
Passing	NAS, NDT	NAS	NAS	ALC
Turning	NAS, NDT	NAS	NAS	
Merging	NAS, NDT	NAS	NAS	ALC
Changing Lanes	NAS, NDT	NAS	NAS	ALC
Braking to avoid an obstacle	NAS, NDT	NAS		

Note—NAS, NDT, and WC are used to indicate how the intent could adapt the system. NAS indicates that the intent could be used for Nuisance Alert Suppression. NDT indicates that the intent could be used to manage the Non-Driving Task demand (e.g., call screening). ALC indicates that the intent could be used as a direct input into the alert level calculation.

8.3 INTENT INFERENCE

This Section will discuss data that may be informative with respect to the task of inferring driver intention. Because most of the intent list of section 8.2.3 involves different types of lane changes, this section will begin by discussing the recent work of Lee et al. (2002) addressing naturalistic lane changes. Eye tracking is likely to be a pivotal sensor for the inference of intent and therefore this section will also include a discussion on eye-movements. Because many researchers have already begun to explore methods of inferring intent, this section will conclude with a discussion of previous work in the domain of intent inference.

8.3.1 Lane Change

Wierwille (1984) described the execution of lane change as essentially a two-stage process:

1. Apply steering input, introducing deviation of heading that will cause lateral deviation
2. As the vehicle approaches the desired lateral position in the adjacent lane, the driver applies a steering input in the opposite direction to cancel the heading deviation.

A passing maneuver involves two successive lane changes, one into the adjacent lane and after the principal-other-vehicle (POV) is passed, another back in front of the (POV) in the original lane (Wierwille, 1984). Chovan et al. (1994) explained that a merge maneuver is kinematically similar to a lane-change, and differs only by the environment, which often involves larger rates of closure (e.g., host vehicle moving into a faster moving traffic stream). It is likely that intent to merge versus intent to change lanes can only be discriminated based on properties of the environment. A turn, though kinematically very different from a prototypical lane change, involves changing lanes into a road that travels in a different direction. Lane changes are frequently made immediately prior to a turning maneuver, so that the host vehicle is located in an appropriate lane (e.g., turn-only lane) before the turning maneuver is initiated.

Chovan et al. described a simple model of ideal lane change behavior. The steps prior to the execution of the lane change can be summarized as follows:

- Assess whether the lane change is legal (e.g., lane markings)
  - If not, do not proceed with lane change

- Assess whether the change is appropriate at the current time
  - Check mirrors for rear-approaching vehicles
  - Look in blind spot for vehicle in target lane
  - Look ahead for lead vehicle in target lane
  - Look in far-adjacent lane for vehicles entering new lane
  - Identify roadway limitations for lane change

- If appropriate, signal intent to change lanes (turn signal) and execute maneuver

This model is for an ideal lane change, and does not necessarily represent typical driving behavior (Chovan et al., 1994). If such behavior was typical, the inference of intent to change lanes could simply involve monitoring the turn signal. The turn signal is still likely to be a useful indication, however, an intent inference algorithm cannot rely on the activation of a turn signal. Because drivers infrequently proceed through all of the ideal lane change steps, a more sophisticated algorithm for intent inference is required, which monitors several of the aforementioned steps, such as checking mirrors and blind spot. A description of natural lane changing behavior would therefore be useful for examining strategies for lane change inference.

In a recent study by Lee et al. (2002), 16 commuters were provided with instrumented passenger vehicles to commute to and from their workplaces. During the ten days of recording per driver, a total of 8667 lane changes were recorded. This was the most thorough and naturalistic study on lane change that has been conducted to date, and is likely to be representative of real world lane change behavior. Previous studies included shorter recording durations, where subjects were probably still becoming accustomed to the instrumented vehicle and were probably still quite cognizant of the fact that they were being monitored (e.g., Mourant and Donahue, 1974) and several other studies examined lane changes in a driving simulator (e.g., Salvucci, Boer, & Liu, 2001) where lane-change behavior could exhibit different characteristics. Lee et al.'s (2002) study is also quite unique in the comprehensiveness of the vehicle instrumentation, including cameras and radars in all relevant directions. These data are likely to be valuable for this task and will be discussed throughout this section.

During Lee et al.'s 8667 lane changes, the average lane change rate was found to be 1 per 2.8 miles of driving. Twelve percent of lane changes involved passing and three percent of lane changes involved traveling through multiple lanes. The motive for changing lanes appeared to be a slower lead vehicle ahead in 37 percent of all lane changes. These slower-lead-vehicle lane changes are likely to be quite important for FCW nuisance alert suppression, given that the host vehicle is closing in on the lead vehicle. Of the slow lead vehicle changes, 67 percent were single lane changes, 32 percent involved passing and 92 percent were to the left. Turn signals were used on average 44 percent of the time, with extremely large individual differences. The use of turn signals differed between directions of lane change with an average of 48 percent use for left lane changes and 35 percent for right lane changes.

8.3.2 Eye Movements

Whereas the peripheral visual field is of low spatial resolution, receptors in the center of the retina (fovea) provide greater spatial resolution, and allow the observer to discriminate finer details. When an object in the periphery attracts the observer's attention, the observer tends to make eye-movements in order to ensure that the image of the object falls on the foveal receptors. The control of fixation is organized into several specialized types of eye-movements, which allow the observer to extract the greatest amount of information from the image (Hart, 1992). The types of movements include fixation maintenance, saccadic eye-movements, and smooth-pursuit eye-movements. Fixation movements serve the function of sustaining objects in a stable position on the foveal receptors of the retina, allowing for higher visual acuity. Saccadic movements are extremely rapid and voluntary in contrast to smooth pursuit eye-movements that involve a smoother tracking of objects. Although smooth-pursuit tracking of smaller objects is partially under the observer's voluntary control, observers are usually unable to suppress tracking of larger objects (Hart, 1992).

Observer's eyes typically move toward an object to which the observer is attending and therefore eye-movements can provide insight about the mental processes of the observer. A pattern of eye-movements offers the potential to detect not only how the observer is allocating attention but may also provide information about the observer's intentions for the future. Before an action is performed, the observer must usually focus on those aspects of the environment that either afford or do not afford the intended action. For example, a driver who intends to pass a lead vehicle on a two-lane road is likely to attend to the oncoming lane of traffic and to the type of center road markings. A system that is sensitive to the eye-movements that coincide with information detection, may be able to predict the action before the action is initiated in any overt manner.

To discriminate between situations where a driver intends a specific action versus those in which the driver does not, we must learn how the measured variables are different from one intention to another. The system not only requires information regarding the pattern of variables during an intention, but also how those measures can vary during baseline driving. Many researchers have studied eye-movements during driving as a function of varying tasks. For example, Recarte and Nunes (2000) investigated the effects of mental tasks on visual search behavior while driving. They found that the position variability in drivers' eye-movements greatly decreases during a mental imagery task, suggesting that the "inspection window" was reduced during high levels of cognitive workload. Mourant and Rockwell (1970) explained that the peripheral area of eye tends to monitor lane position, vehicles, and road signs and when the situation requires a more detailed analysis, the fovea is directed toward the target for closer examination. Underwood, Chapman, Crundall, Cooper, and Wallen (1999) studied driver eye-movements during curve negotiation, observing that drivers tend to look at the tangent point of the curve when negotiating curves in order to provide information about the required steering wheel input.

Tijerina (1999) examined drivers' visual behavior during car following. Drivers' glances away from the road had a mean duration of 0.6 s, with a 5^{th} percentile of 0.17 s and a 95^{th} percentile of 1.47 s. Left mirror glances were of similar duration to the average glances away from the road, with a mean of 0.56 s. Tijerina observed that glances away from the forward roadway tended to coincide with a zero range-rate to the lead vehicle. Glances away from the forward roadway were directed at varying locations, with between 28 and 33 percent directed at the center mirror, between 11 and 18 percent directed at the left mirror, between 7 and 15 percent directed over the driver's left shoulder, between 4 and 10 percent directed at the right mirror and between 3 and 4 percent directed over the driver's right shoulder. These data suggest large differences between the use of the left, center, and right mirrors.

Several researchers have specifically studied driver eye-movements during lane change maneuvers. For example, Carter and Laya (1998) studied driving on the road and in a driving simulator while drivers either maintained their current lane or passed a lead vehicle. During normal lane maintenance, the focus of expansion of the optical array (the point to which the driver is headed) attracted 70 percent of the driver's forward glances, and half of the remaining percentage (15 percent) were directed toward the speedometer. They observed that drivers spent significantly more time glancing at the left-hand lane and rear-view mirror and significantly less time glancing at the speedometer during overtaking compared with normal lane-keeping.

Mourant and Donahue (1974) examined the mirror-sampling behavior of drivers during the 5-s prior to lane change maneuvers compared to baseline driving. Nine subjects drove a predetermined 13.5-mi highway route in Michigan. Lee, Olsen, and Wierwille (2002) examined the eye-movements of drivers during the 3-s prior to lane changes during naturalistic driving. The results of their glance analyses are presented in Table 8.6. In the Lee et al. study where a right-side mirror was present, the probability of using this mirror during the 3-s prior to changing lanes was quite low (0.21) and drivers instead appeared to rely on the rear-view mirror (probability of 0.55). By comparing Mourant and Donahue's lane change data with their baseline data (straight), it is evident that drivers glanced at the relevant-side and rear-view mirrors more frequently during the 5 s prior to lane changes than during 5-s straight intervals.

Table 8.6. Glance Data from Lee et a. (2004) and Mourant & Donahue (1974) Lane Change Studies

		Lee et al. (2004) 3 s Before Maneuver		Mourant & Donahue (1974) 5 s Before Maneuver				
		Left	Right	Straight[4]	Left	Left Merge	Right	Right Merge
forward[1]	probability[3]	1	1					
	# glances	2.34	2.03					
	duration (s)	1.98	2.44					
relevant[2] side mirror	probability[3]	0.52	0.21					
	# glances	1.25	1	0.09	1.38	2.44	0	0
	duration (s)	0.83	0.67	0.88	1.02	1.08	0	0
rear view mirror	probability[3]	0.53	0.55					
	# glances	1.36	1.56	0.22	0.76	0.66	2.6	2.48
	duration (s)	0.78	0.94	0.78	0.74	0.82	0.88	0.93
blindspot	probability[3]	0.27	0.14					
	# glances	1.01	1.25	0	0.3	0.34	0.33	0.44
	duration (s)	0.64	0.8	0	1.52	1.31	1.09	1.14

1. Glances to the forward region were not examined in the Mourant & Donahue study.
2. The vehicle in the Mourant & Donahue study was not equipped with a right-side mirror.
3. The probability that the driver glanced at the region was not examined in Mourant & Donahue (1974).
4. The glance data for the Straight maneuver (during no lane change) is derived by dividing the glance behavior values during periods of no lane change by the approximate number of 5-s intervals during this total period (214).

8.3.3 Prior Intent Inference Research

Several researchers have investigated the inference of driver intention. As a part of the European Union PROMETHEUS program, the Driver's Warning Assistant (DWA) detected driver intention in order to improve the cooperation between driver and vehicle (Geiser and Nirshcl, 1993). The DWA system was developed to assess the state of the driver, using information such as individual characteristics, available resources, and driver intent. Although the details of this system were not disclosed, it used information regarding the state of the vehicle, driver, and environment to infer driver intent. The list of intentions included stopping, lane changing, and overtaking.

For early inference of lateral maneuvers, many researchers have used steering input or vehicle heading information. For example, Goldman et al. (1995) developed a Maneuver Intent Recognition (MIR) system to supply information to a Driver-Adaptive Warning System (DAWS). The goal of this research was to use learning algorithms to tailor safety warnings to the individual and situation. The MIR system used yaw and heading information to detect an intention to change lanes. A layer of neural networks monitored the driver's lane following information to detect significant deviation from the typical lane following behavior. When the lane following model failed to fit the observed performance, the MIR system triggered an intention to maneuver. This system achieved accuracies of 92 to 98 percent, depending on the driver. However, because the system relied on yaw and heading information to detect driver intention, the MIR system could only detect the maneuver after the maneuver had already been initiated. For this reason, Goldman et al.'s approach represents detection of the maneuver rather than making an inference that the driver intends to engage in the maneuver.

In work that was closely associated with that of the DAWS work, Salvucci (2004) also used steering wheel inputs as the basis of detecting that the driver was engaged in a lane change maneuver. In his simulator-evaluation study, Salvucci recorded that the detection accuracy was 65 percent at the moment that the vehicle first began to move laterally and that this increased to 90 percent accuracy 1 s after the maneuver had begun or by the time the vehicle moved ¼ of the lane width. Although this algorithm appears to be a reliable and early means of detecting a maneuver, the success in the driving simulator must be verified on real roadways, where the data are likely to be far more noisy (Lee et al., 2004).

Yuhara and Tajima (2001) applied a similar approach to provide input into their adaptive steering system. Their intent recognition algorithm used only steering-wheel angle. A high-pass digital filter was applied to the steering-wheel data, and an auto-regressive moving average model was fitted to the time-series data. The detection of lane change was triggered when the moving average of the squared prediction error reached a specific threshold. Because the system used the high-frequency component of steering wheel angle to predict lane change, the system was not sensitive to slow lane changes, where the steering wheel angle changed gradually. The other weakness of this approach is that, like Goldman et al.'s (1995) approach, Yuhara and Tajima (2001) could only recognize lane change after the maneuver had already been initiated.

Both Chovan et al. (1994) and Lee et al. (2002) had argued that it was difficult to discriminate a lane change from normal lane keeping based on vehicle trajectory alone because of the variability in typical lane-keeping behavior. Lee et al. also applied this argument to the use of steering-wheel data. An algorithm that fuses a larger amount of information is likely to be more sensitive and support earlier detection of lateral maneuvers. For example, Tijerina (1999b) suggested that a vector of indicators could be used that might include "a following distance of less than x feet and a closing rate of greater than y feet per second to the vehicle ahead, an upcoming exit given the chosen route in an Automated Traveler Information System (ATIS), an obstacle detected in the roadway ahead, etc." (p. 144). Tijerina's hypothetical example demonstrates the importance of fusing different sources of data, including data that corresponds with the affordances of the environment (e.g., upcoming exit).

Takahashi (2000) developed an intent inference system to detect a driver's intention to accelerate or decelerate. Arguing that driver intention is heavily constrained by the affordances, Takahashi used fuzzy logic operating on environmental variables to predict whether the driver would accelerate or decelerate. This application is more closely related to a driver's intention to "brake to avoid an obstacle" than the lateral maneuvers included in Table 8.3. Takahashi's work demonstrated how useful an analysis of affordances is for the prediction of driver intent.

The other obvious source of data for the inference of intent is the driver's eye movements immediately prior to the maneuver. Lee et al. (2002) explained:

> *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.* (p. 15)

The data generated by Lee et al.'s naturalistic lane change study will be an extremely valuable source for investigating the eye movements that immediately precede a lane change maneuver and specify intent. As this was not the focus of Lee et al.'s research, they did not search for eye-movement patterns that may be reliably diagnostic of driver intentions.

However, Liu (1999) did conduct an investigation of eye-movement patterns for the purposes of intent inference. Based on Liu's previous work (Liu, Veltri, and Pentland, 1998), which demonstrated how a Markovian analysis of fixation patterns could identify different driving situations, Liu used Hidden Markov Dynamic Models (HMDMs) for the real-time detection of lane changes. Liu described the HMDM process as involving a learning stage, where the HMDM parameters are estimated based on a training set of observation vectors and a recognition stage, which involves Viterbi matching of real-time Markovian matrices with the HMDM models of specific maneuvers. Although the details of Liu's analysis were not disclosed, they used information that including vehicle heading and acceleration in addition to driver gaze coordinates. Liu tested his lane-change detection algorithm in the driving simulator and observed accuracies ranging from 50 to 70 percent within 3 s of the initiation of the maneuver. Because this method allows much faster detection than merely relying on vehicle trajectory or steering wheel angle, Liu argued that eye-movement data enables prediction of the anticipated maneuver rather than quickly recognizing the task after it has already been initiated. Liu suggested that multiple models might be required for different drivers, due to the individual differences of Markov matrices.

This section has discussed different sources of data that could be useful for the diagnosis of driver intentions to maneuver and has concluded with a discussion of previous attempts to detect driver intent. The next section will summarize the Task 8 literature review, propose hypotheses for the inference of intent, and propose a research strategy for Task 8.

8.4 HYPOTHESES FOR INTENT INFERENCE

The preceding sections have discussed applications for intent inference and information that could support the inference of driver intention. Intent information could be used by the distraction mitigation system to suppress lower priority information (e.g., incoming phone call) and warnings (e.g., distracted driver warning). Intent information could also be used extensively by the safety warning countermeasure system. Not only could driver intention information be used to suppress nuisance alerts (e.g., for FCW), but in some cases the inference of driver intention could be used as a major input into the alert algorithm (e.g., lane change warning). Table 8.3 summarized the list of intents that Task 8 will attempt to detect and the manner in which the intents could be used.

Section 8.3 discussed sources of information that could be used to trigger driver intent inference. Ideal lane change behavior was contrasted with the actual lane-change behavior that was observed in Lee et al.'s (2002) naturalistic lane change study. The eye-movement behavior of drivers preceding maneuvers was discussed and Section 8.3 was concluded with a discussion of previous attempts to detect intent in the literature. Whereas some researchers (e.g., Yuhara and Tajima, 2001) focused on the early detection of the maneuver after the maneuver had already been initiated, other researchers (e.g., Liu 1999) focused on inferring the intent before the maneuver was initiated. Liu (1999) used Hidden Markov Models of eye-fixation behavior to detect the intent to change lanes 3 s before the maneuver was initiated.

This section will conclude the Task 8 literature review by proposing some hypotheses for the inference of driver intent and propose a strategy for researching this problem.

8.4.1 Hypotheses for Intent Inference

Based on the literature that has been reviewed in the previous sections, a matrix has been developed that organizes the potentially diagnostic sources of information as a function of the type of maneuver that is intended. Table 8.6 includes each of the intent classes from Table 8.3, including the following maneuvers: steering to avoid an obstacle, passing, turning, merging, changing lanes, and braking to avoid an obstacle. The potentially diagnostic sources of information that have been suggested in the various approaches of other researchers have been organized into five categories, including affordances, motive, kinematics, controls, and fixation.

The work of Takahashi (2000) suggests that affordances could be a useful source of information to aid in driver-intent inference. As 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, motive information may suggest 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 data may override that of motive.

Table 8.6. Hypothesized diagnostic measures for intent inference

		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.

The motive category arises in response to the work of Lee et al. (2004), who demonstrate a relatively small set of motives for their naturalistic lane change data set and the work of Tijerina (1999b), who suggested using information such as distance to the vehicle ahead or navigation destination information. These sources of information may provide a reason for why the host vehicle will engage in a maneuver. For example, if the host vehicle is closing in quickly on a lead vehicle, a lane change, passing, braking, or avoidance maneuver may be more probable. If the FCW system has activated an imminent alert and there is insufficient time to brake, this may predict the intention to engage in an avoidance maneuver. Navigation information may be used to help trigger the intent to turn. For example, if the navigation route requires that the driver make a right hand turn in the near future, it is likely that the driver intends to turn. Like affordances, in most cases motive in isolation will not be sufficient for reliably inferring driver intentions. Instead, this type of data will most likely be used in combination with other sources of information such as kinematic, control, and fixation data.

Kinematic variables are likely to be the latest variables to develop into predictors of driver intention, because usually the driver must have already begun to execute the maneuver for kinematic variables (e.g., lateral position) to be diagnostic. For example, the yaw-rate or lead-vehicle azimuth angle will begin to change as a lane-change maneuver is initiated. Relying on these data may represent maneuver detection rather than intent inference per se. As the time progresses toward the completion of the maneuver, emerging sources of information become increasingly reliable. In the trade-off between early inference and inference accuracy, relying on kinematic variables might represent the higher-accuracy/later-inference side of the spectrum. It is for this reason that kinematic variables may be considered to be the last line of defense for intent inference. In some cases, however, the driver may slow down or speed up before engaging in the maneuver. Lee et al. observed 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.

The work of Salvucci and colleagues (e.g., Salvucci, Boer, & Liu, 2001; Salvucci & Liu, 2002; Salvucci, 2004) suggests that monitoring driver controls, including throttle and steering-wheel angle may support early maneuver detection and possibly intent inference. Sudden releases of the gas pedal may indicate that the driver intends to brake or is about to engage in an avoidance maneuver. Changes in throttle position may indicate that the driver is intending to change lanes. Salvucci and Liu (2002) observed a small reduction in throttle position just prior to lane changes in their driving simulator. Salvucci and Liu (2002) also observed slight shifts in steering wheel angle just prior to lane changes and then a sinusoidal pattern during the lane change, that Salvucci (2004) used as the primary source of information to detect lane changes. Brake pedal activation may often precede avoidance maneuvers, turns, merges, and lane changes and is the latest and most certain source of information to indicate that the driver intends to brake. Although turn signals are not always used before a lane-change maneuver, when a turn signal is activated, the driver almost always intends to avoid, pass, turn, merge, or change lanes. In the 44 percent of cases (Lee et al., 2002) where the driver does use a turn signal, it is expected that intent inference will be accurate and effective, provided that the turn signal is activated prior to the maneuver. In the 56 percent of cases where the driver does not, the intent inference system must rely on other sources of information to trigger the inference of intent.

The work of several researchers (especially Mourant and Donahue, 1974 and Lee et al., 2002) strongly suggests that driver fixation or glance behavior could be useful for inferring driver intention. When a driver intends to engage in any kind of driving maneuver, it is likely that the driver will glance toward the forward scene. Lee et al. (2002) indicated that there is a probability of one that there will be at least one glance toward the forward scene before a lane change. This is also likely to be true for avoidance and braking maneuvers. Therefore, it is likely that a glance toward the forward scene will be a necessary but not sufficient criterion for the inference of any type of intent. When drivers intend to engage in any deviation from normal lane keeping, it is likely that they will sample information in the direction of where they intend to travel. For example, it is likely that the driver will monitor the oncoming lane of traffic (Salvucci, Boer, & Liu, 2001) and the interior or left side mirror (Mourant and Donahue,

1974) before a lane change. Drivers' fixation behavior most likely represents a source of earlier-inference/lower-accuracy data for intent inference.

Using fixation behavior alone for the inference of driver intention is likely to lead to a large number of false positives (infer intent when no intent exists). Because intent may be used as a basis for suppressing warnings to the driver, false positives may result in the failure to detect actual threats to the driver. Therefore, it is important that intent-inference algorithms fuse multiple sources of information together. The inference of a given intent might require consensus between several types of variables. For example, for the system to detect intent to change lanes, the algorithm might require the appropriate affordance (a lane into which the host vehicle can change), a motive for a lane change (e.g., slow lead vehicle or change into turn lane), and the appropriate fixation behavior (e.g., sampling of the roadway in the direction of the lane change and of the forward scene). The early inference of driver intention is a challenging problem and success will require the fusion of multiple sources of information.

8.4.2 Strategy for Intent Inference

The development of intent inference algorithms will be a combination of theory-driven and data-driven approaches. The initial effort will involve examining data sets for patterns of data that precede the targeted maneuvers. This process will be guided by the information that has been discussed in this literature review, however, patterns that are expected based on theory and prior research will need to be verified on the new data sets. One approach to the data analysis will be to derive zero and first-order Markov matrices of fixation transitions, based on the work of Liu (1999). Whereas the zero-order Markov matrices will contain the probability that the driver will glance at a certain location, the first-order Markov matrices will contain the conditional probabilities that the driver will glance at a new location given the current eye-fixation location. The data sets that involve the targeted maneuvers will be compared with data sets that involve normal lane-keeping behavior in search of discriminating differences. The algorithm will use Table 8.6 as a starting point to guide the discriminative analysis.

This task will make use of other available data sets. One such data set is that of the Lee et al. (2002) naturalistic lane change study. This data set includes 500 samples of radar, kinematic, and variables during the 3 s immediately prior to lane change maneuvers. It would have been ideal if the data set included these variables for a longer period of time than 3 s prior to the maneuver; however, the purpose of Lee et al.'s study was different from the purposes of this task. Although the 3-s duration will impose a limitation on these analyses, this data set represents the most naturalistic and comprehensive set of data that could be used for the inference of the intent to change lanes. In many lane changes, especially those that are more urgent, the intent to change lanes will precede the maneuver by less than 3 s. Analyses will investigate how quickly the intent to change lanes can be accurately detected, beginning 3-s before the maneuver was initiated and ending when the maneuver was completed. Another limitation of Lee et al's data set is that it does not include baseline cases, where no maneuver is intended. These baseline cases will have to come from a different data source.

After the analysis has revealed reliable differences between the maneuver and baseline situations, the test and refinement phase of data analysis will begin. During this phase, preliminary algorithms will be programmed to run on the data sets, and the success of the algorithms will be analyzed. Success will be defined according to a signal detection theory framework. Table 8.7 displays the matrix of four possible outcomes.

Table 8.7. Signal detection framework for an analysis of intent inference success

		Intent Inference Algorithm Classification	
		Intends Maneuver (i)	Doesn't Intend Maneuver (n)
Actual Driver Intent	Intends Maneuver (I)	P(i/I) Hit	P(n/I) Miss
	Doesn't Intend Maneuver (N)	P(i/N) False Alarm	P(n/N) Correct Rejection

In the signal detection framework, there are two possible correct responses and two possible types of errors. Correct responses include hits, where the system detects an intention when an intention exists, and correct rejections, where the system accurately detects that there is no current intent to maneuver. The two types of errors include misses, where the system detects no intention, when an intention currently exists and false alarms, where the system detects an intention when no intention is currently present. Based on the false alarm rate and hit rate, the properties d' and β can be estimated. Whereas d' quantifies the precision of the detection algorithm, β independently quantifies the bias on the detection system, or the favoring of one type of error versus another. Using this framework, the precision of the algorithm to detect differences can be analyzed independently from the bias of the algorithm. Of the two types of errors, it is likely that false alarms can have greater negative consequences than misses. If driver intent is used to suppress warnings, whereas intent-inference misses could lead to a smaller reduction of nuisance alerts, intent-inference false alarms could lead to failures of the warning system to detect an actual danger to the driver. The success of the algorithm will therefore be judged and refined based on both d' and β.

During the test and refinement phase of algorithm development, iterative modifications will be made to the algorithms on the basis of algorithm performance, and the modified versions will be rerun on the data sets. During the iterative and cyclical process of test and refinement, it is hoped that the performance of algorithms will be improved in terms of both precision (d') and bias in favor of misses versus false alarms (β). If the data from Task 3 (Performance) becomes available in sufficient time, the test and refinement phase will also be extended to the Task 3 data set. Task 3 will be concluded with the development of a set of intent-inference algorithms corresponding with the six types of driver intent and a description of the algorithm performance. In Phase II of the SAVE-IT Program, the algorithms will be encoded into a test vehicle and algorithm performance will be more thoroughly validated.

REFERENCES

Billings, C. E. (1997). *Aviation Automation: The Search for a Human-Centered Approach*. Lawrence Erlbaum Associates, Publishers Mahwah, New Jersey

Boer, E. R. (2001). Behavioral entropy as a measure of driving performance. *Proceedings of the First International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design,* 225-229.

Brunson, S. J., Kyle, E. M., Phamdo, N. C., & G. R. Preziotti (2002). *Alert Algorithm Development Program: NHTSA Rear-end Collision Alert Algorithm Final Report*. National Highway Transportation Safety Administration, Washington DC., report no. DOT HS 809 526.

Carter, C. J. & Laya, O. (1998). Driver's visual search in a field situation and in a driving simulator. *Vision in Vehicles, 6*, 21-31.

Chovan, J. D., Tijerina, L., Alexander, G., & Hendricks, D. L. (1994). *Examination of Lane Change Crashes and Potential IVHS Countermeasures* (DOT HS 808 071). National Highway Traffic Safety Administration, Washington, DC:, http://www. itsdocs.fhwa.dot. gov/

Ervin, R., Sayer, J., & LeBlanc, D. (2003). *Field Operational Test Task Summary. Presentation made to National Highway Transportation Safety Administration for the Automotive Collision Avoidance System Field Operational Test (ACAS FOT) Program Program Review 7*, Jan 29, 2003.

Geiser, G. & Nirschl, G. (1993). Towards a system architecture of driver's warning assistant. In Parkes, A.M. & Franzen, S. (Eds.) *Driving future vehicles*, London: Taylor & Francis (pp. 251-263).

Gibson, J. J. (1986). *The Ecological Approach to Visual Perception*. Hillsdale, NJ: Lawrence Erlbaum Associates, Inc. (Original work published 1979)

Goldman, R., Miller, C., Harp, S., Plochner, T. (1995). *Idea Project Final Report. Contract ITS-7*. Transportation Research Board, National Research Council, Washington, DC.

Hart, W. M. (1992). Adler's Physiology of the Eye (9th Ed.). Mosby: St Louis, MO.

Hoedemaeker, M., de Ridder, S. N., & Janssen, W. H. (2002). *Review of European Human Factors Research on Adaptive Interface Technologies for Automobiles.* TNO-report. TM-02-C031.

Kiefer, R., LeBlanc, D., Palmer, M., Salinger, J., Deering, R., & Shulman, M. (1999). *Development and validation of functional definitions and evaluation procedures for collision warning/avoidance systems*. Washington D.C.: U.S. Department of Transportation, report no. DOT-HS-808-964.

LeBlanc, D. J., Bareket, Z., Ervin, R. D., & Fancher, P. (2002). Scenario-based analysis of forward crash warning system performance in naturalistic driving. *Paper presented at the 9th World Congress on Intelligent Transport Systems.*

Lee, J. D., McGehee, D. V., Brown, T. L, & Raby, M. (1999*). Review of RECAS display interface issues and algorithms: Task No. 2.* National Highway Transportation Safety Administration, Washington DC., report no. DTNH22-95-D-07168.

Lee, S. E., Olsen, E. C. B., Wierwille, W. W. (2004). *A Comprehensive Examination of Naturalistic Lane-Changes,* NHTSA DTNH22-00-C-07007

Liu, A. (1999). Towards predicting driver's intentions from patterns of eye fixations. *Vision in Vehicles, 7*, 205-212.

Liu, A., Veltri, L.,and Pentland, A. P. (1998). Modelling changes in eye fixation patterns while driving. *Vision in Vehicles, 6*, 13-20.

Mazzae, E. N. & Garrott, W. R. (1995). *Development of Performance Specifications for Collision Avoidance Systems for Lane Change, Merging, and Backing. Task 3 – Human Factors Assessment of Driver Interfaces of Existing Collision Avoidance Systems (Interim Report).* National Highway Traffic Safety Administration, Washington, DC:, http://www. itsdocs.fhwa.dot.gov/

Merriam-Webster (1998). *Merriam-Webster's Collegiate Dictionary*, Tenth Edition, Merriam-Webster, Inc.

Mourant, R. R. & Donohue, R. J. (1974). *Mirror Sampling Characteristics of Drivers (SAE paper 740964)*. Warrendale, PA: Society of Automotive Engineers.

Mourant, R. R. & Rockwell, T. H. (1970). Mapping eye-movement patterns to the Visual Scene in Driving: An Exploratory Study, *Human Factors, 12*, 81-87.

NHTSA Benefits Working Group (1996). *Preliminary Assessment of Crash Avoidance Systems Benefits.* National Highway Traffic Safety Administration, Washington, DC:, http://www. itsdocs.fhwa.dot.gov/

Pierowicz, J., Jocoy, E., Lloyd, M., Bittner, A., Pirson, B. (2000). *Intersection Collision Avoidance Using ITS Countermeasures. Final Report*. DOT HS 809 171. National Highway Traffic Safety Administration, Washington, DC:, http://www. itsdocs.fhwa.dot. gov/

Piersma E. H. (1993). Adaptive interfaces and support systems in future vehicles. In Parkes, A.M. & Franzen, S. (Eds.) *Driving future vehicles*, London: Taylor & Francis (pp. 321 – 332).

Pomerleau, D., Jochem, T., Thorpe, C., Batavia, P., Pape, D., Hadden, J., McMillan, N, Brown, N., and Everson, J. (1999). *Run-off-road collision avoidance using IVHS countermeasures (Final report).* (DOT HS 809 170). National Highway Traffic Safety Administration, Washington, DC:, http://www. itsdocs.fhwa.dot. gov/

Rasmussen, J. (1986*). Information processing and human-machine interaction: An approach to cognitive engineering*. New York: North Holland.

Recarte, M. A. & Nunes, L. M. (2000). Effects of verbal and spatial-imagery tasks on eye fixations while driving. *Journal of Experimental Psychology, Applied, 6*, 31-43.

Salvucci, D. D. (2004). Inferring driver intent: A case study in lane-change detection. *Proceedings of the Human Factors Ergonomics Society 48th Annual Meeting*.

Salvucci, D. D., Boer, E. R., & Liu, A. (2001). Toward an integrated model of driver behavior in a cognitive architecture. *Transportation Research Record, 1779.*

Salvucci, D. D., & Liu, A. (2002). The time course of a lane change: Driver control and eye-movement behavior. *Transportation Research Part F, 5,* 123-132.

Takahashi, H., Kuroda, K. 2000. Intelligent sensing system to infer driver's intention. Nissan Motor Company (Japan) 7 p. *Automotive Electronics: Delivering Technology's Promise. Warrendale, SAE, 2000*, p. 375-381. Report No. SAE 2000-01-C056.

Tijerina, L. (1999a). Driver Eye Glance Behavior During Car Following on the Road, *SAE International Congress and Exposition, report no. SAE 1999-01-1300*, p. 1 - 5.

Tijerina, L. (1999b). Modeling the effectiveness of crash avoidance systems that support driver maneuver decisions: lane change crash avoidance example and issues. *ITS Journal, 5*, 127-161.

Tijerina, L., Garrot, R. W., Glecker, M., Stolzfus, D., & Parmer, E. (1997). *Van and Passenger Car Driver Eye Glance Behavior During Lane Change Decision Phase.* Transportation Research Center, Inc. and National Highway Transportation Safety Administration, Vehicle Research and Test Center.

Tijerina, L. & Hetrick, S. (1997). Analytical evaluation of warning onset rules for lane change crash avoidance systems. *Proceedings of the Human Factors and Ergonomics Society 41st Annual Meeting, Volume 2*. Santa Monica, Human Factors and Ergonomics Society, 949-953.

Underwood, G., Chapman, P., Crundall, D., Cooper, D., & Wallen, R. (1999). The visual control of steering and driving: where do we look when negotiating curves. *Vision in Vehicles, 7*, 245-253

Wierwille, W. W. (1984) Driver steering performance. In G. A. Peters and B. J. Peters (Eds.) *Automotive Engineering and Litigation: Volume 1* (pp 407-434). New York: Garland Law Publishing.

Young, S. K., Eberhard, C. D., & Moffa, P. J. (1995). *Development of performance specifications for collision avoidance systems for lane change, merging and backing. Task 2: functional goals establishment. Interim report.* National Highway Traffic Safety Administration, Office of Collision Avoidance Research, Washington, D.C. report no. DOT HS 808 432.

Yuhara, N. & Tajima, J. (2001). Advanced steering system adaptable to lateral control task and driver's intention. *Vehicle System Dynamics, 36*, 119-158.