SAVE-IT

SAfety VEhicles using adaptive Interface Technology (Task 5)

Final Report: Phase 1

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5.0 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.

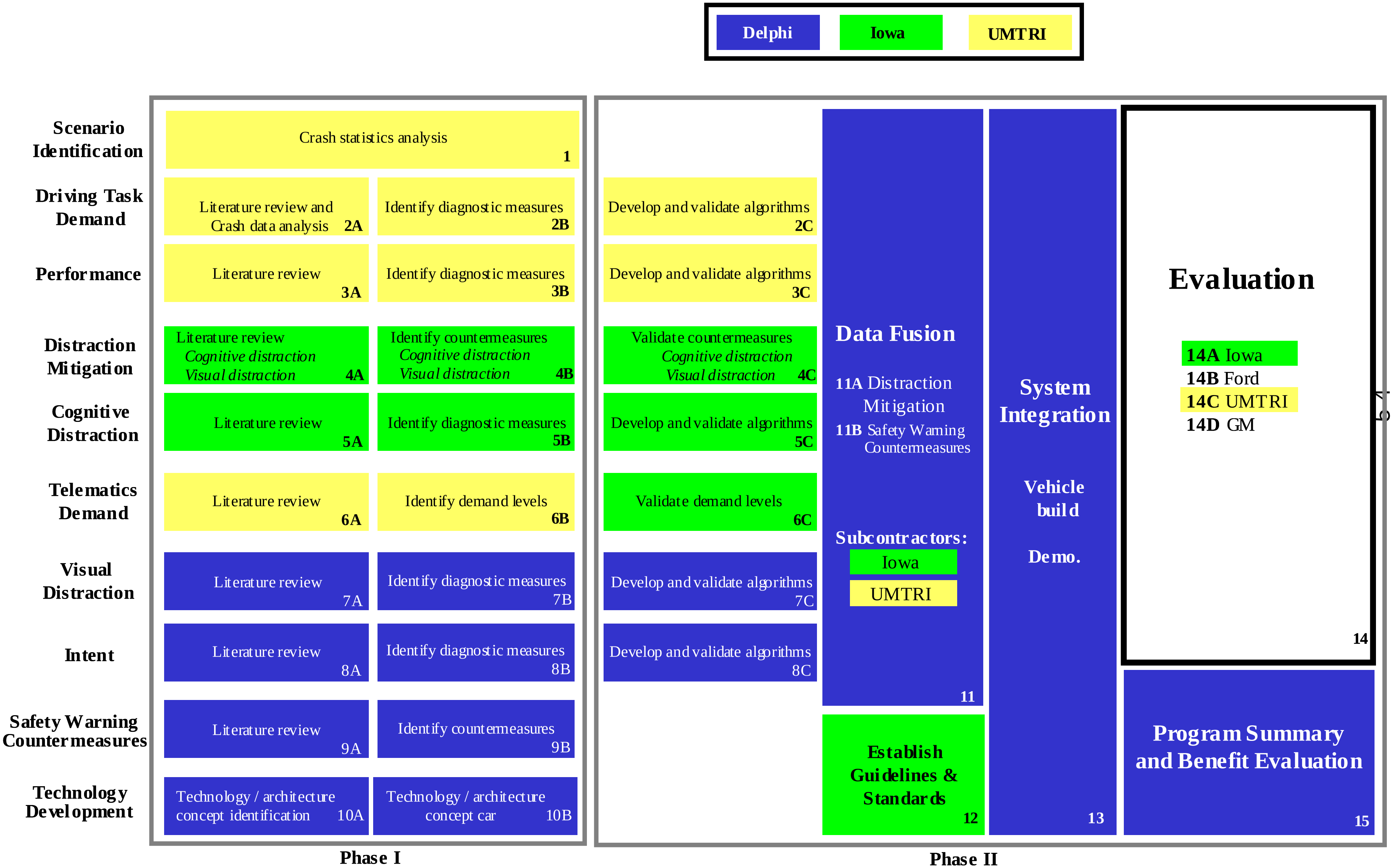


Figure i: SAVE-IT tasks

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 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

[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.

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.

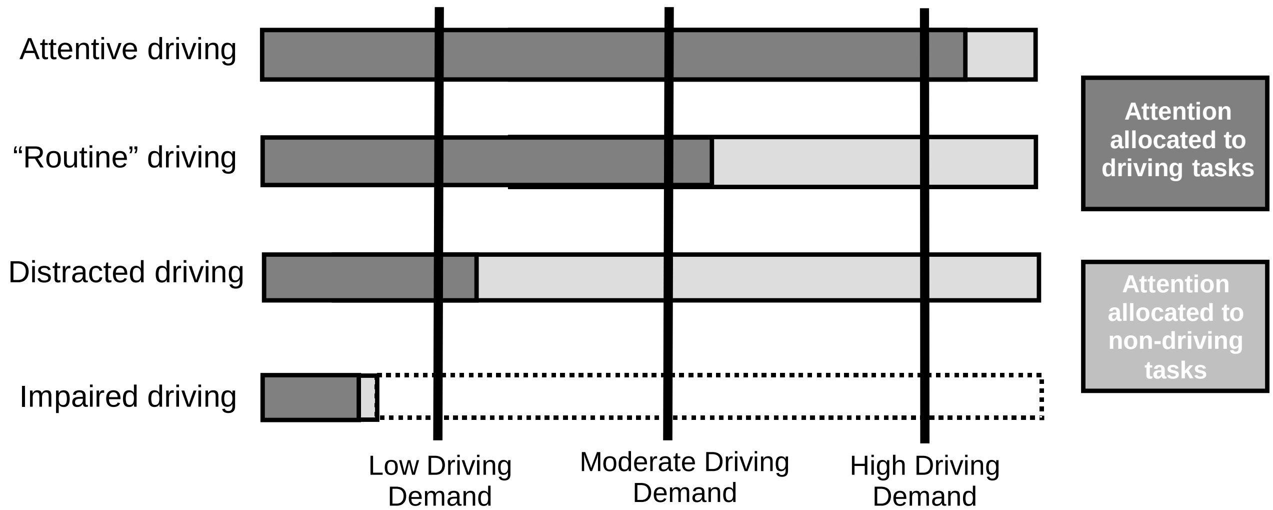


Figure ii. Attention allocation to driving and non-driving tasks

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.

<u>Commonalities Among Driving Simulators and Eye Tracking Systems In Phase I</u> 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.

<u>Common Dependent Variables</u> 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.

<u>Common Driving Scenarios</u> 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.

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

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

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

The Content and Structure of the Report

The report submitted herein is a final report for Task 5b that documents the research progress to date (March 2003-March 2004) in Phase I. In this report, the major results from the literature review are summarized to determine the research needs for the present study, the experimental methods and resultant data are described, diagnostic measures are identified, and human factors recommendations are offered.

5.1 INTRODUCTION

Computer, software, telecommunications, and automotive companies have begun to develop In-Vehicle Information System (IVIS) functions in anticipation of a \$15 – \$100 billion IVIS market (Ashley, 2001). Longer commute times, pressures for increased productivity, and increasingly powerful technology all stimulate IVIS development because IVIS technology enables drivers to use driving time to do tasks otherwise done at the office. Even without the widespread use of IVIS functions, approximately 6 million traffic accidents cause roughly 42,000 deaths and \$150 billion in costs each year (Bureau, 1998). Between 13 and 50 percent of crashes are attributed to driver distraction, resulting in estimates of as many as 10,000 lives lost and as much as \$40 billion in damages each year (Stutts, Reinfurt, Staplin, & Rodgman, 2001; Sussman, Bishop, Madnick, & Walter, 1985; Wang, Knipling, & Goodman, 1996). Driver inattention is a particularly large contributor to rear end collisions, where it is sited as a contributing factor in approximately 60% of such collisions (Knipling et al., 1993). Because distraction is a substantial contributor to crashes, particularly rear end collisions, and the distraction potential of cognitive demands are well documented (Haigney & Westerman, 2001), the increasing prevalence and complexity of in-vehicle technology will likely increase the safety problems of distraction. A promising strategy to address this problem is to measure the degree of distraction in real time and use it to guide adaptive in-vehicle technologies to mitigate the effects of distraction.

The overall objective of this task was to use the diagnostic measures of cognitive distraction identified by Task 5a (Cognitive Distraction Literature Review) to develop an algorithm that predicts decrements in driving performance. Driving performance is operationalized as the reaction time to driving events that require a response by the driver. Figure 5.1 shows the general strategy adopted to predict decrements in reaction time that might result from cognitive distraction. Three distinct sources of data were combined: driver state variables, including measures of eye gaze and physiology; driver performance variables, including measures of steering and speed control; and in-vehicle information system state variables, including expected cognitive transactions associated with particular interactions with the IVIS(s). Specifically, our objectives were to develop an experiment that created a measurable degree of distraction, to evaluate dependent measures associated with this distraction, and to develop an algorithm that can predict distraction based on those measures.

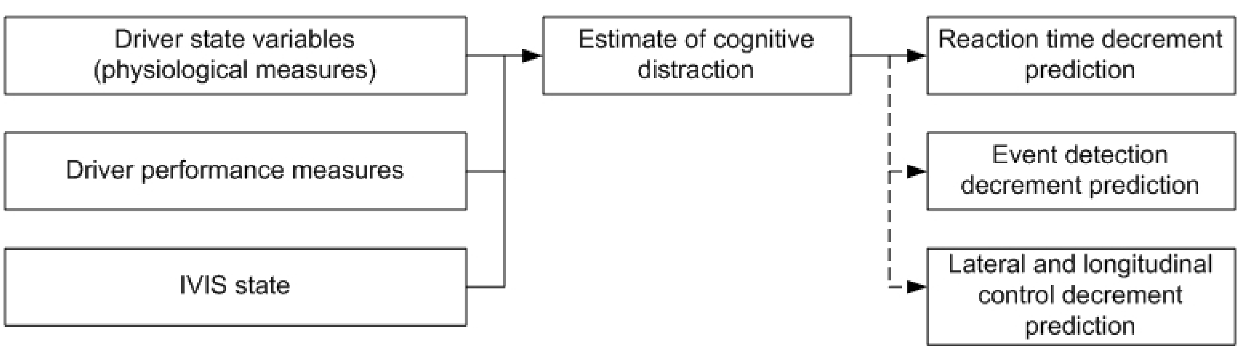


Figure 5.1. Convergent measures of cognitive distraction combine to predict reaction time decrement.

5.2 TYPES OF DISTRACTION, ITS MEASUREMENT AND PREDICTION

Distraction can appear in various forms, including visual, manual or biomechanical, auditory, and cognitive distraction (Ranney, Mazzae, Garrott, & Goodman, 2000). Cognitive distraction occurs when cognitive activity associated with a non-driving task interferes with perception, processing, and/or response to the roadway environment. One important implication from this definition is that distraction itself cannot be measured. Distraction is a relational property between the driver's cognitive activity, the demands of the driving tasks, and the demands of the IVIS tasks.

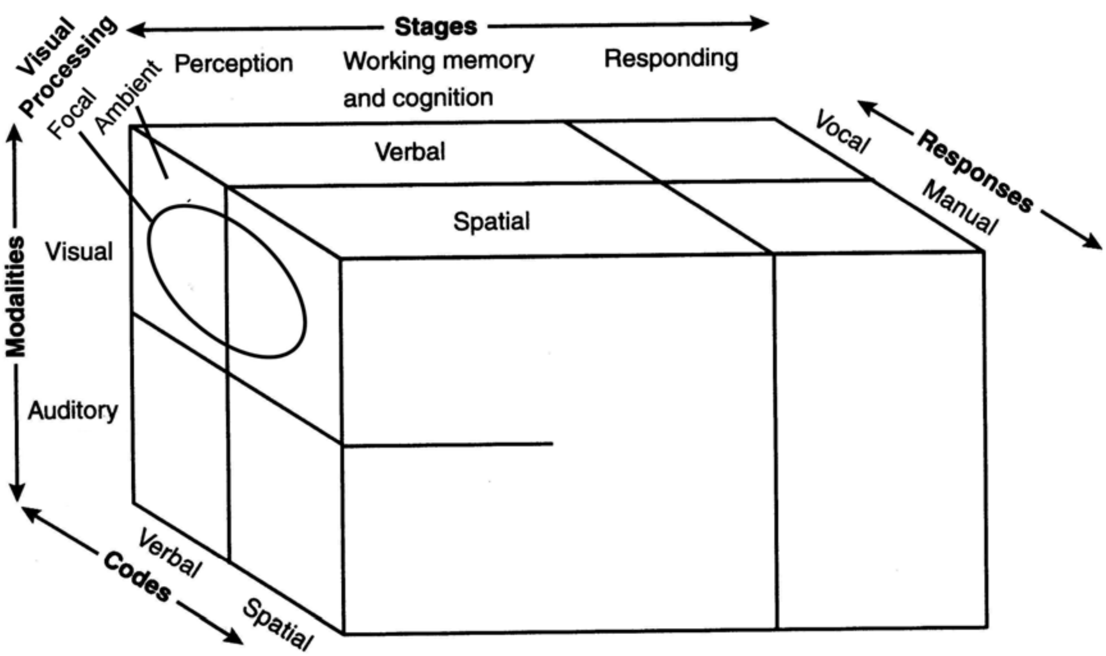


Figure 5.2. Three-dimensional representation of the structure of multiple resources.

Distraction is the result of conflicts between the demands of driving and the demands of IVIS interactions. Multiple resource theory (MRT) provides a framework for understanding situations where the demands of cognitive tasks may overload drivers' capabilities and interfere with safety-critical driving tasks (Wickens, 1984, 2002). Multiple resource models can be used to predict whether interference is likely or unlikely to occur in dual-task situations. With this approach, dual-task performance is governed by multiple and independent attentional limited capacity resources. MRT states that these resources are located on several different dimensions that can be allocated to different tasks, as shown in Figure 5.2. The four dimensions are perceptual modality, code, stage, and response modality. A performance decrement in the dual-task situation is seen when tasks compete for the same resource within a dimension. A large number of experiments have suggested that a processing bottleneck occurs during response selection (Pashler, 1998) so this attentional resource may be particularly limited. Findings by Strayer and Johnston (2001) support this view, as participants performed significantly worse on a driving task while in a conversation condition as compared to a condition where they listened to a book on tape for comprehension. Thus, this bottleneck can affect tasks that do not share perceptual or coding resources. The degree to which the central processing bottleneck dominates driver performance compared to the other dimensions of the MRT has not been established.

Although MRT provides a useful basis for understanding how driving and in-vehicle tasks interact to create distraction-related decrements in driving performance, it focuses on how attentional resources are shared in a relatively basic dual-task scenario. However, driving and interacting with one or more IVIS creates a much more complex situation. Driving alone involves multiple tasks which can be arranged in a hierarchy according to the various levels of drivers' goals. Near the bottom are control tasks, such as speed selection, speed control, and lane keeping, which are required to meet the driver's goal of keeping the car on the roadway. Another level of driving goals involves includes those associated with tactical driving, such as hazard detection and lane selection. Finally there are tasks, such as visual search for landmarks, which are associated with navigation and the driver's high-level goals (e.g. trying to find a gas station with acceptable prices). A similar hierarchy of tasks and goals could be used to describe IVIS functions. Therefore, the distraction-related decrements in driving may not be predicted by performance decrements of two simple tasks.

A preliminary conceptual model that integrates many of the theoretical considerations regarding driver distraction is shown in Figure 5.3. The model distinguishes between two distinct levels of behavior associated with distraction. Tactical behavior describes driving and IVIS tasks at a relatively molar level, with a time scale of 5-60 seconds. In contrast, the control behavior describes these tasks at a relatively micro level, with a time scale of 0.5-5 seconds. Each of these levels has qualitatively different performance metrics, effects on driving, and opportunities to mitigate distraction. At the same time, both levels share similarities regarding the closed loop nature of the interactions, the fact that roadway and IVIS dynamics are critical determinants of the demand, and the fact that performance depends on the joint demands of the roadway and IVIS, which can be combined using a conflict matrix.

Figure 5.3 shows that six links connect the tactical and control behaviors. The tactical level influences the control level by partially determining roadway and IVIS demand. Roadway demand is determined by speed and headway selections and IVIS demand is partially determined by the decision to engage in IVIS activities. Tactical behavior also determines the effort invested and how that effort is allocated between driving and IVIS interactions. Control behavior also influences the tactical behavior. Violations of safety margins and breakdowns in IVIS interactions may lead to changes in tactical behavior that affect IVIS and roadway demand, as well as effort investment and resource allocation.

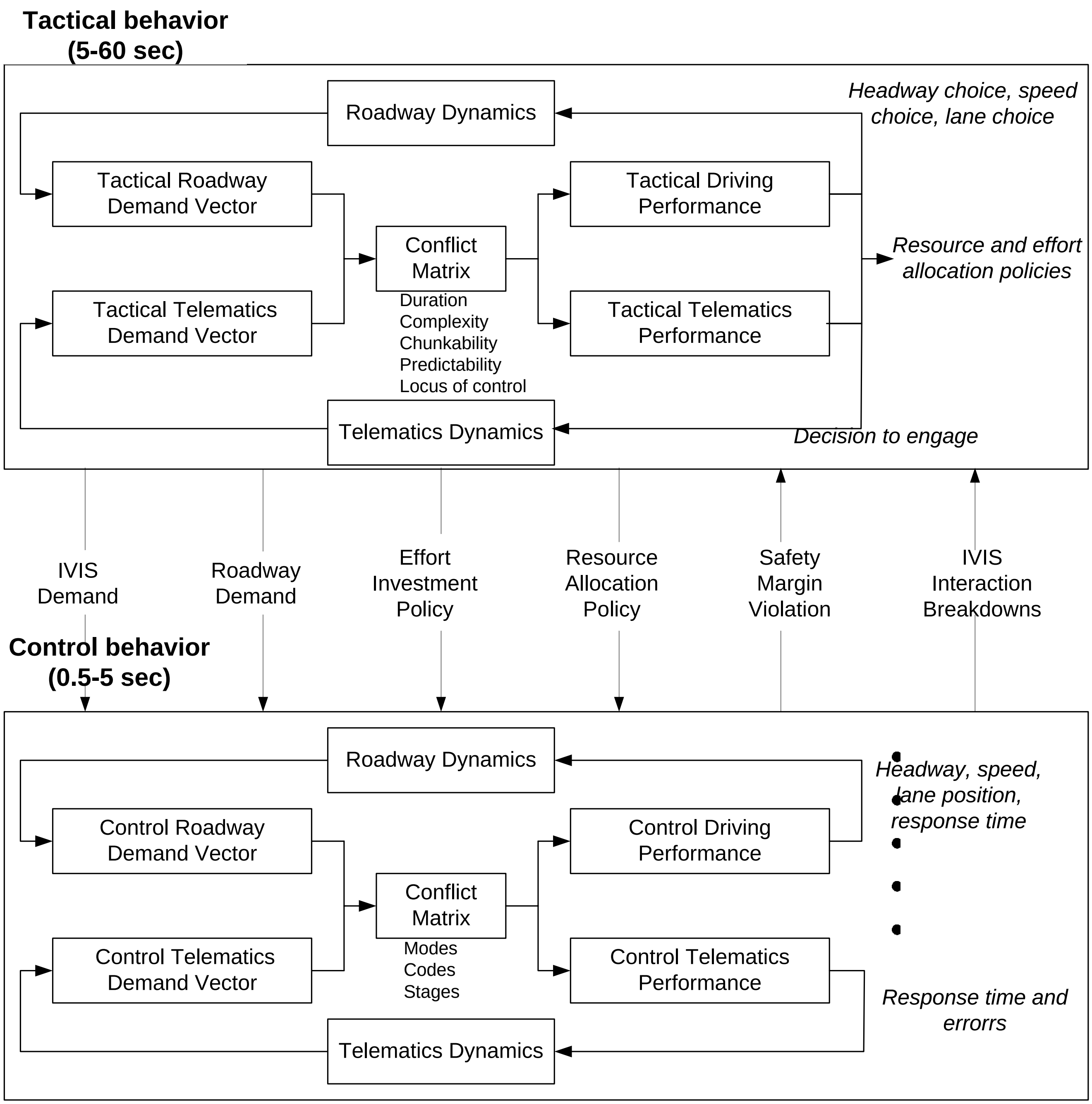


Figure 5.3. Integrated model of distraction, showing the interaction of behavior at the tactical and control levels on driving and IVIS performance.

Common to both tactical and control behavior is assumption that IVIS and roadway demands can be represented by a vector and that the performance can be estimated by assessing the joint demands using a conflict matrix. For control behavior, this approach is not new and vectors defined by the MRT dimensions of modes, codes, and stages predict performance decrements (Nakayama, Futami, Nakamura, & Boer, 1999b; Wickens, 2002). For tactical behavior this approach has not been used; however, potential dimensions to describe task demands at this level include: task duration, complexity, divisibility (chunkability), predictability, and locus of control. Identifying these dimensions and how they interact to govern tactical IVIS and driving performance is an important research issue that will be addressed in an experiment in the second phase of the Save-It program.

In this experiment we examine the how the demands of IVIS tasks influence driving performance at the control and tactical levels. The IVIS task used in this experiment mimics a system that might provide information about restaurants to drivers as they enter a city. The system provided a realistic, yet controlled system to investigate how typical IVIS demands might affect driving performance. In particular, we hypothesize that the perceptual stage (listening to IVIS messages) will conflict relatively little with the driving control tasks of braking when a lead vehicle decelerates. According to the central bottleneck theory of attention, generating responses is expected to conflict most, and driving and complex response selection will be the most distracting. Eye gaze measures will be more sensitive to spatial tasks than to verbal tasks. Task complexity will interact with the braking event type such that complex tasks will disproportionately disrupt response to braking events that require a tactical response. Overall, we expect to generate systematic decrements in driving performance with the IVIS tasks and these decrements will be correlated with systematic changes in eye gaze patterns.

5.3 METHODS

5.3.1 Participants

Twenty-two drivers, eleven male and eleven female, participated in this experiment. All were between the ages of 36 and 55 (M = 44.5, STD = 6.14), possessed a valid U.S. driver's license, and had at least 5 years of driving experience. All drove at least 5 times a week and were native English speakers. The participants were compensated monetarily for their participation.

5.3.2 Experimental Design

The experimental design consisted of twelve within-subject conditions and two baseline conditions. Combinations of three within-subject independent variables defined the experimental conditions:

- Lead vehicle braking task (control or tactical).
- Multiple resource theory (MRT) dimensions of the IVIS task (verbal or spatial, perceptual or response selection).
- Response selection complexity (simple or complex, nested within the Response condition).

5.3.2.1 Braking tasks

The driving scenarios included two kinds of braking events, control and tactical. In control events the lead vehicle appeared to brake randomly; the events could not be anticipated and driver response time depended on control-level driving skills. In tactical events the lead vehicle braked in response to a vehicle that changed lanes or pulled out onto the roadway in front of the vehicle ahead of the driver. In these situations, driver response time depended on tactical level driving skills that govern anticipation of roadway events. When the lead vehicle began to change lanes, an attentive driver could use this cue to anticipate the need of the lead vehicle to brake. The timing of the braking events was arranged such that the braking event was contained within either the perceptual or response stage of an IVIS message or during the period when the driver was not performing any IVIS task.

Both the control and tactical braking events were generated with the press of a button by an experimenter. Two seconds after the generation of the lane changing tactical event and three seconds after the generation of the pullout tactical event, the lead vehicle braked at a rate of 0.2 g. For some of the tactical braking events, the lead vehicle had to brake prematurely at a rate higher than 0.2 g in order to avoid collision with the tactical lead vehicle. As a result, not all of the tactical braking events allowed adequate anticipation time. Anticipation time for each event was calculated and events for which anticipation time was greater than or equal to 1.5 seconds were coded as tactical. All others were coded as control events.

5.3.2.2 IVIS tasks

Multiple resource theory (Wickens, 2002) was used to define messages according to the dimensions of verbal/spatial codes and perceptual/response selection stages. The messages were either verbal or spatial in nature and required the participant to listen to the message (perception condition) and respond to questions presented about the message (response condition). All messages and questions were presented as .wav files that were created using the Ultra Hal Text-to-Speech Reader, Version 1.0, created by Zabaware, Inc. (available at http://www.zabaware.com). The voice chosen was "Sam," a Microsoft SAP14 Text-to-Speech Synthesis Machine described as an adult male, clear, low-accented North American English native voice. The playing of the messages and the questions was executed by an experimenter through the use of a Visual Basic interface. Each message was played twice and the verbal and spatial messages were presented between trials with two trials for each type of message.

The verbal messages presented information about the cost, quality, and wait time at three different restaurants in the form of dollar signs, stars, and long or short wait time. The questions asked about cost, quality, and wait time in units of dollars, positive recommendations, and minutes, respectively. As a result, the participant had to verbally transform the information presented in the message into the same form as the question in order to formulate their answer. The presentation of each verbal message lasted approximately 70 seconds.

The spatial messages presented directions to three restaurants in the form of right and left turns from a start point. While listening to the instructions for the spatial messages, the participant was shown the map presented in Figure 5.4 and instructed to begin at the start point facing north. The message told the participant whether to turn right or left at each of the next two intersections and then whether to turn left or right in order to enter the parking lot of the restaurant. The questions asked about the locations of the restaurants in relation to the start point in the form of the cardinal directions (north, south, east, and west). As a result, the participant had to spatially transform the information presented in the message into the same form as the question in order to formulate their answer. The presentation of each spatial message lasted approximately 80 seconds.

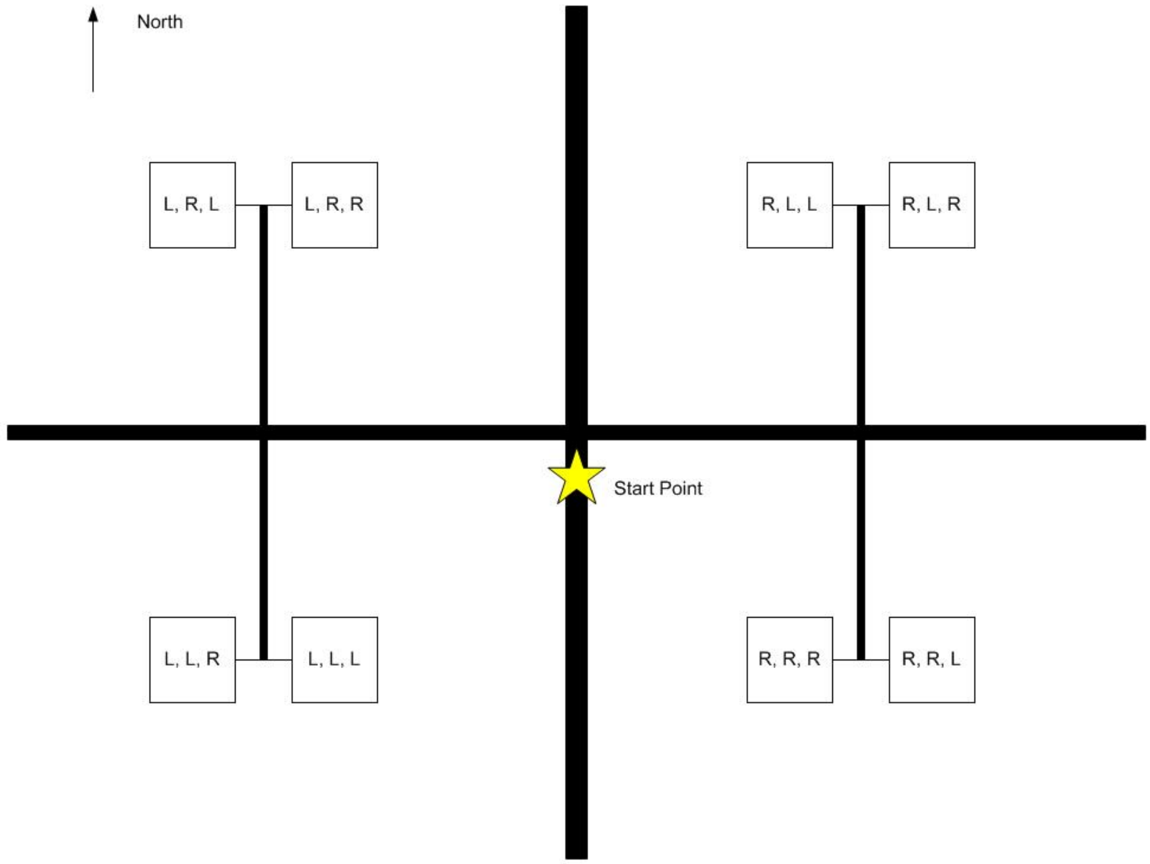


Figure 5.4. Shows the locations referred to in the spatial messages, with "L" and "R" referring to the sequence of left and right turns needed to reach that destination.

The response task was implemented at two levels of difficulty, simple or complex. A simple response required the participant to answer the questions based upon a single criteria or location. A complex response required the participant to consider two criteria (e.g., Name one of the restaurants that have an average entrée cost of less than $10 and have more than 10 positive recommendations?). Each response period lasted approximately 60 seconds. The next message was played approximately 30 seconds after the completion of the response period. Extra compensation, based on the accuracy with which participants completed the response stage of IVIS message tasks, was given to motivate the participants to try their best.

Combining the three parameters (verbal/spatial, perception/response, and simple/complex nested within response) resulted in six different in-vehicle system message conditions. Combining these six message conditions with the two kinds of braking events resulted in twelve within-subject experimental conditions. Each drive included six of these twelve conditions since verbal and spatial conditions were presented in different drives. Two braking events, one of each type, without a message condition were added as control events. These events were executed after the completion of the response period and before the next message and constituted one of the two kinds of baseline drives, the IVIS baseline. Table 5.1 describes the within-subject experimental conditions for one drive. Each of the four experimental drives were approximately 18 minutes in length and included the presentation of six messages, their corresponding questions, and twelve braking events. A fifth baseline drive contained six braking events and no IVIS tasks and lasted approximately 9 minutes. These events constitute the no IVIS baseline. The order of presentation of the fives drives was randomized.

Table 5.1. Experimental Conditions.

Condition number	Braking event	Message coding	Stage	Level	Frequency per trial
1	Tactical	Verbal	Perceptual	----	1
2	Tactical	Verbal	Response	Simple	1
3	Tactical	Verbal	Response	Complex	1
4	Control	Verbal	Perceptual	----	1
5	Control	Verbal	Response	Simple	1
6	Control	Verbal	Response	Complex	1
7	Tactical	----	----	----	3
8	Control	----	----	----	3
Total Events					**12**

5.3.3 Dependent Measures

The main dependent measures collected from the driving tasks were the accelerator release time, brake reaction time, and minimum time to collision (TTC). Accelerator release time is defined as the time from when the lead vehicle began to brake until the participant released the accelerator. Brake reaction time is the time from when the lead vehicle began to brake until the participant began to press the brake. These measures were calculated for each braking event. Eye movements were also monitored with a Seeing Machines eye tracker and FaceLAB software. Electrocardiogram data were collected using BIOPAC Systems, Inc.'s AcqKnowledge software. Finally, driving performance measures such as lane position, steering wheel position, speed, and accelerator position were recorded.

5.3.4 Driving Simulator

A fixed-based, medium-fidelity driving simulator was used to conduct the experiment. The simulator uses a 1992 Mercury Sable vehicle cab that has been modified to include a 50-degree visual field of view, force feedback steering wheel, and a rich audio environment. The fully textured graphics are generated by state-of-the-art PC hardware that delivers a 60 Hz frame rate at 1024 x 768 resolution. The simulator is powered by Global Sim, Inc.'s DriveSafety™ Research Simulator, a fully integrated, high-performance driving simulation system designed for use in ground vehicle research and training applications. The HyperDrive™ Authoring Suite was used to create driving scenarios, and all graphics for roadway layouts, markings, and signage conform to American Association of State Highway and Transportation Officials (AASHTO) and Manual of Uniform Traffic Control Devices (MUTCD) design standards. Driving data was collected at 60 Hz.

All scenarios took place on a suburban arterial street with two lanes in each direction. This environment was chosen because it provided a realistic environment to present drivers with lead vehicle braking events that were either cued by other events in the environment (i.e., a car pulling out in front of the lead vehicle) or randomly occurring without cues. The drive began with the participant vehicle parked in the right lane of the street behind the lead vehicle. Along the right hand side of the road was a fairly continuous row of parked cars. In the left lane was a steady flow of traffic traveling at 33 mph. The instrument panel was covered and the participant was instructed to follow the lead vehicle and drive at approximately the same speed as the surrounding traffic. The lead vehicle maintained a fixed headway of 1.8 seconds.

5.3.5 Procedure

After arriving at the laboratory and reading and signing an informed consent document, the participant practiced the both the verbal and spatial message tasks. Then the participant drove a 10 minute practice drive. During the second half of the drive the participant practiced the IVIS task with two more messages and the corresponding questions. Next, the participant was fitted with electrodes to enable the monitoring of cardiac rhythms and markers to enhance the tracking performance of the Seeing Machines eye tracker. The eye tracker was calibrated for the participant and then the participant completed each of the five scenarios. Following each scenario, the participant completed a Rating Scale Mental Effort (RSME) questionnaire (De Waard, 1996).

5.4 RESULTS AND DISCUSSION

5.4.1 Driver distraction and IVIS interactions

Driver distraction was assessed by driver's response to the periodic braking of the lead vehicle. Braking responses during IVIS interactions were compared to two types of baseline brake response data. Baseline drive braking events occurred during drives with no IVIS interactions throughout the entire drive and are hereafter referred to as the no IVIS baseline. The second type of baseline braking events occurred during the period between IVIS interactions. That is, the drivers were not at the time interacting with the IVIS but did interact with it during other periods of the same drive. Hereafter these baseline events will be called the spatial baseline or the verbal baseline for these events that occurred during a drive with the spatially- or verbally- coded IVIS task, respectively. For all types of baseline conditions, the mean accelerator release and brake reaction times were essentially the same. The accelerator release reaction time was 1.07 seconds for the no IVIS baseline condition, 1.13 seconds for the spatial baseline condition, and 1.11 seconds for the verbal baseline condition, $F(2,41) = 0.20$, $p=0.820$. Similarly, the brake reaction time was unaffected by the various baseline conditions—2.10 seconds for the no IVIS baseline condition, 2.13 seconds for the spatial baseline condition, and 2.20 seconds for the verbal baseline condition, $F(2,38) = 0.41$, $p=0.669$. Thus the braking responses during the no IVIS baseline drive were quite similar to the spatial and verbal baseline responses that occurred between IVIS interactions during the IVIS drives.

As expected, the type of braking task had a large effect on accelerator release and brake reaction times. The mean accelerator release reaction time was 0.84 seconds during the tactical braking events, which could be anticipated, and 1.37 seconds during the control braking events, which could not be anticipated, $F(1,21) = 44.53$, $p<0.0001$. There was no significant interaction between the different baseline conditions and the braking tasks, $F(2,38) = 0.59$, $p=0.560$. The mean brake reaction time was 1.89 seconds during the tactical braking events and 2.37 seconds during the control braking events, $F(1,20) = 32.03$, $p<0.0001$. As with accelerator release reaction time, there was no interaction between the baseline conditions and the braking tasks, $F(2,37) = 0.10$, $p=0.905$. The lack of difference between baseline conditions suggests they can be combined to provide a more precise estimate of driver's baseline braking response. For the rest of this section, unless otherwise noted, references to baseline driving performance refer to the combined baseline conditions.

Comparing the baseline driving performance to driving performance during IVIS interactions shows that both accelerator release and brake reaction times degraded during IVIS interactions, but only for tactical braking events. The mean accelerator release reaction time was 1.28 seconds during IVIS interactions and 1.10 seconds during baseline driving, $F(1,21) = 11.99$, $p=0.0023$. The mean brake reaction time follows a similar pattern, with longer responses during IVIS interactions (2.32 seconds) compared to the baseline driving (2.14 seconds), $F(1,21) = 8.30$, $p=0.0089$. However, accelerator release reaction time depended on an interaction between braking task and the IVIS task, $F(1,21) = 6.48$, $p=0.019$. The type of braking event did not interact with IVIS interaction for the brake reaction time, $F(1,20) = 1.04$, $p=0.320$. Performance of the IVIS task during the tactical braking events resulted in a substantial increase for accelerator release reaction time of approximately 325 ms $t(21) = 3.72$,

p=0.0013. A similar effect was seen for brake reaction time, with an average increase of 238 ms for tactical braking, $t(20) = 2.41$, p=0.026. The IVIS had little effect on the reaction time during the control braking events, increasing the mean accelerator release time by only 49 ms, $t(21) = 0.77$, p=0.451, and the mean brake reaction time by 113 ms, $t(20) = 1.58$, p=0.130. The longer reaction time for the tactical braking events suggests that the IVIS interactions degrade drivers' ability to anticipate emerging traffic conflicts more than drivers' response to immediate threats.

IVIS interactions were defined in terms of the stage of processing (perception and response), the complexity of the response, and the code of processing (spatial and verbal). None of these factors had a statistically significant effect on accelerator release and brake reaction times.

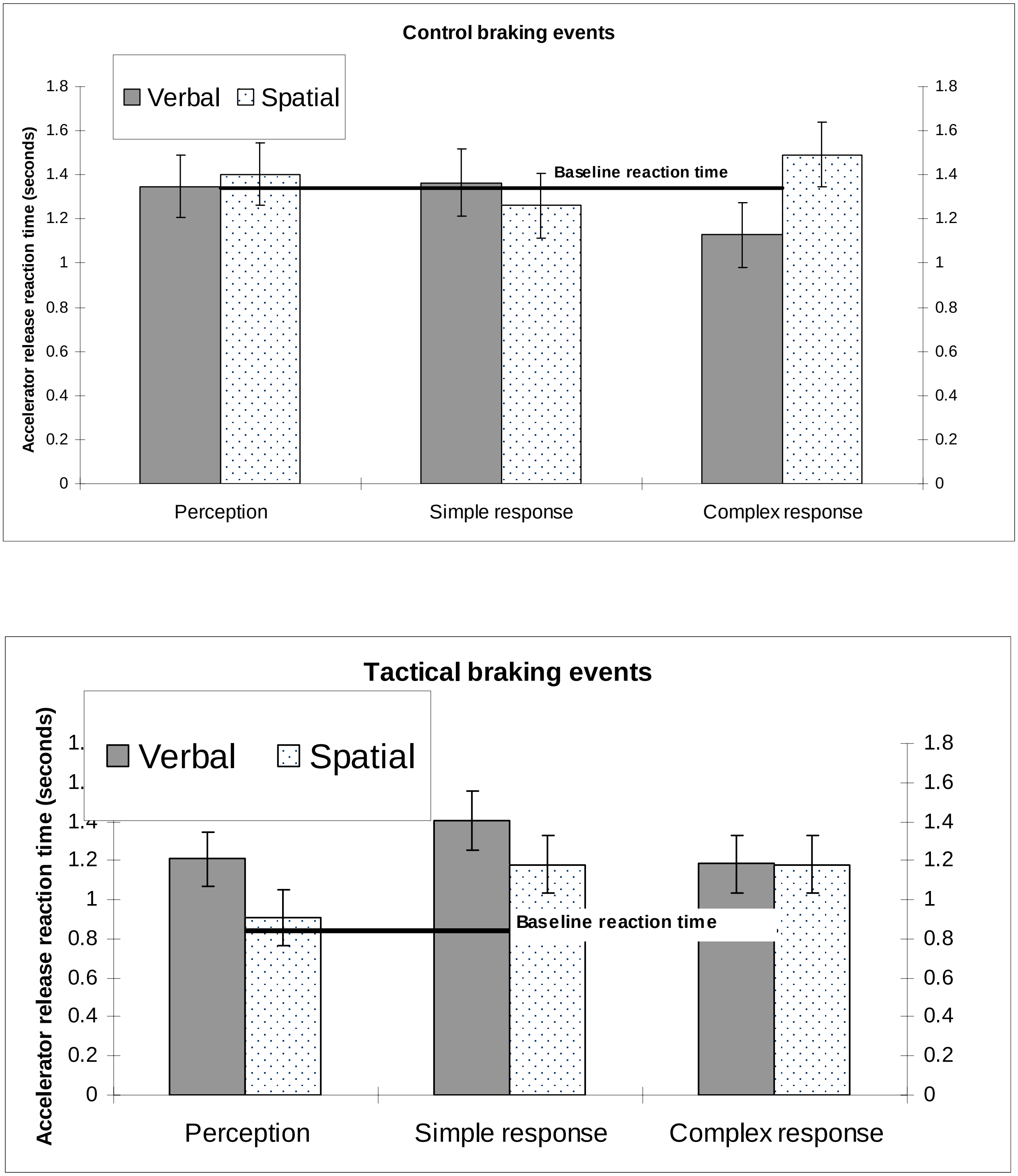


Figure 5.5. The effect of the IVIS interactions relative to the baseline conditions.

Although accelerator release and brake reaction times are not affected by the characteristics of IVIS interactions, these characteristics do affect other important driving performance measures, specifically measures associated with the maintenance of vehicle speed and accelerator position. For example, a main effect of IVIS stage was seen for speed averaged from the beginning of the IVIS stage until the braking event, $F(2,42) = 9.02$, $p=0.0006$. The mean speed was lower when the drivers were responding to the IVIS (15.88 m/s) compared to listening (16.52 m/s) and for the period between IVIS interactions (16.41 m/s). When drivers responded to complex questions they drove more slowly (15.66 m/s) compared to simple questions (16.10 m/s), $F(1,21) = 4.26$, $p=0.0516$. These results, shown in Figure 5.6, support the hypothesis that listening to the messages is less distracting than responding. Because the response stage always followed the perception stage of the IVIS interaction it is likely that the effect of response stage may reflect the time it takes the vehicle speed to drop when the driver becomes distracted rather than any particular demand of perception or response; however, the slightly slower speed during the complex responses suggests that the speed maintenance is also compromised by the demands of responding to the IVIS.

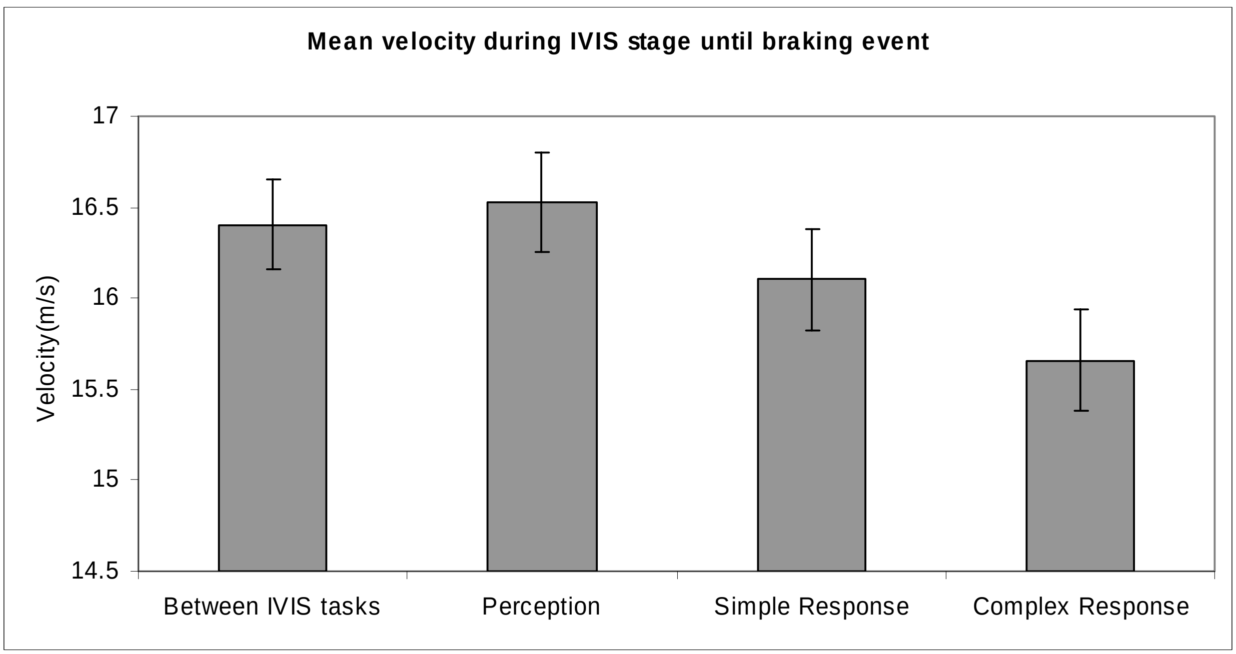


Figure 5.6. The effect of IVIS stage on mean velocity.

The mean accelerator position, during the IVIS interaction until the start of the braking event, shown in Figure 5.7, reveals a highly significant effect of IVIS stage, $F(2,42) = 31.67$, $p<0.0001$. Accelerator position during the period between IVIS interactions (10.2%) was greater than accelerator position during perception (8.5%), $t(42)=5.33$, $p<0.0001$, or response (8.3%), $t(42) = 7.33$, $p<0.0001$. Because the response stage always followed the perception stage, these data, too, may only show the cumulative effect of distraction on the vehicle dynamics rather than the particular effect of one information processing stage or another.

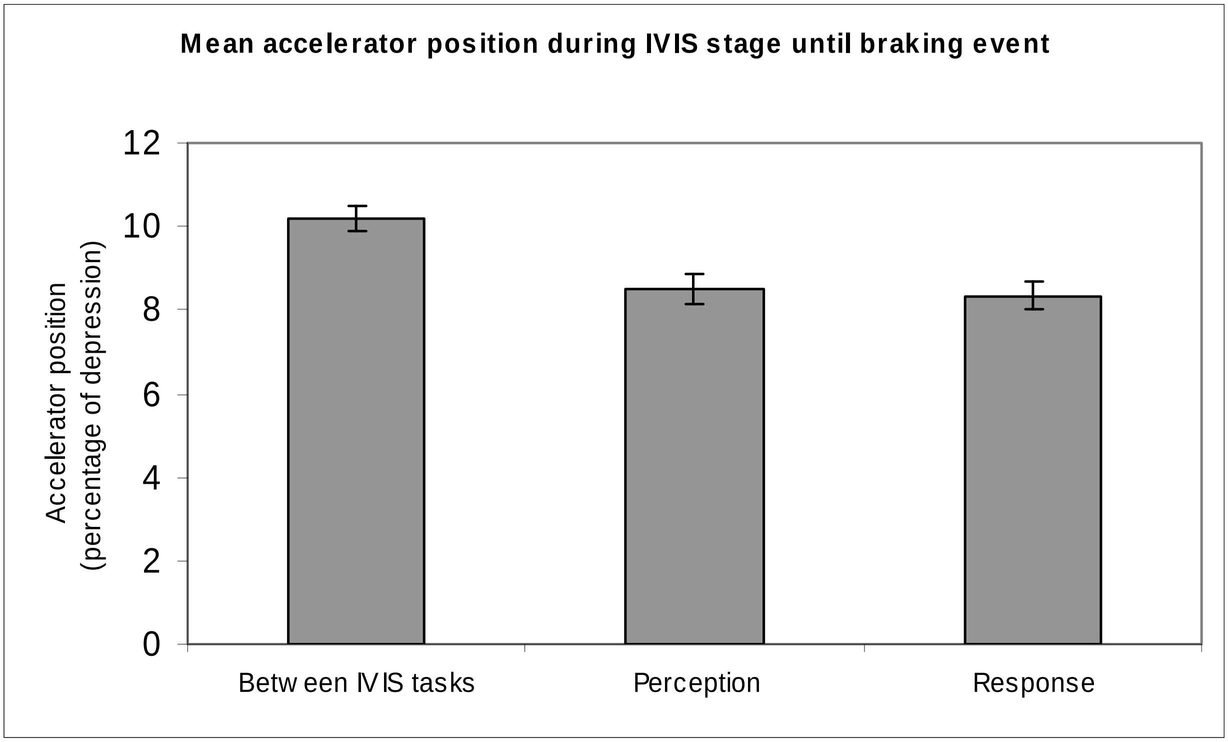


Figure 5.7. The effect of IVIS stage on mean accelerator position.

The variability of the drivers' speed, as measured by the standard deviation of speed from the beginning of the IVIS stage until the initiation of the braking event, shows a very strong effect of stage. As drivers listened to the message, their speed was much more variable (1.18 m/s) compared to when they responded to the message (.69 m/s), $F(1,21) = 76.48$, $p<0.0001$, as shown in Figure 5.8. More complex responses led to greater variability (0.78 m/s) compared to simple responses (0.60 m/s), $F(1,21) = 8.20$, $p=0.0093$.

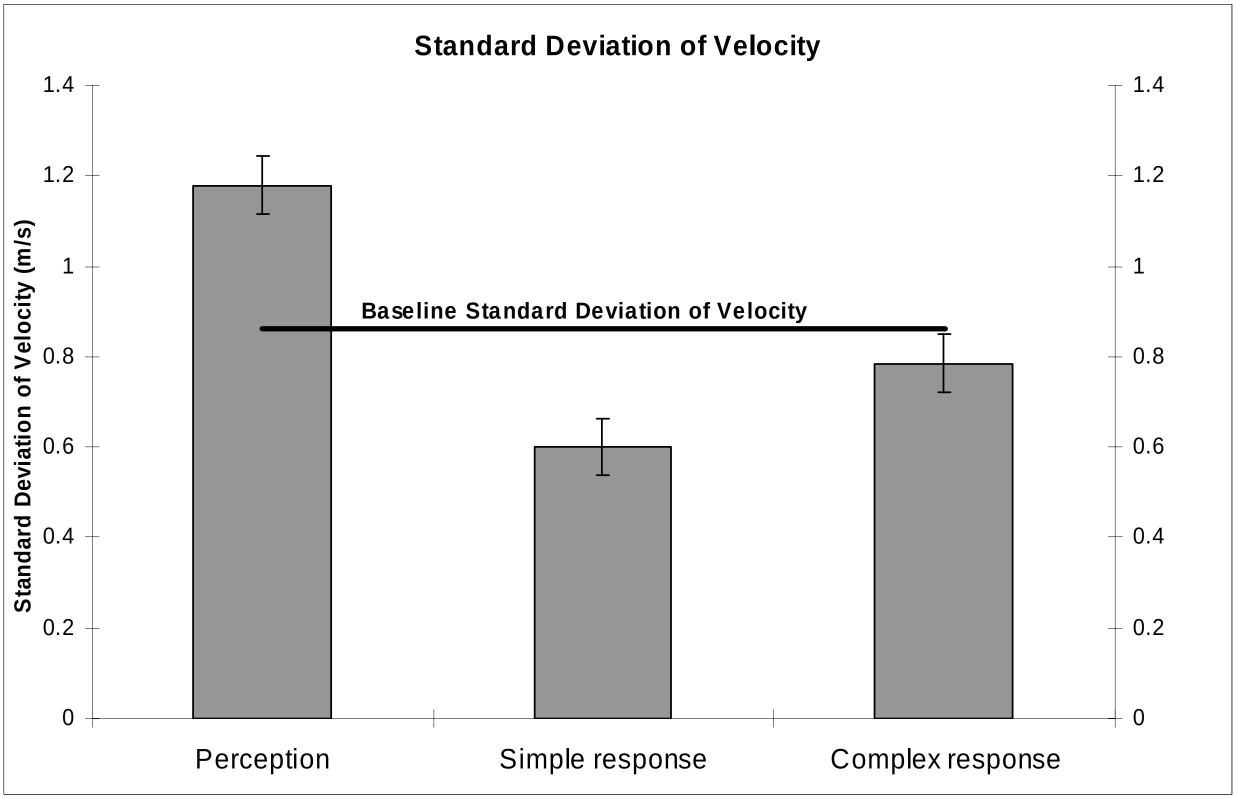


Figure 5.8. Effect of stage on variability of velocity.

The variability in accelerator position, measured as the standard deviation of percentage of accelerator depression from the beginning of the IVIS stage until the initiation of the braking event, shows a similar pattern. While listening to the message, the accelerator position was more variable (4.85%) than while responding to the message (4.05%), $F(1,21) = 14.85$, $p=0.0009$. Variability of the accelerator position was greater during the complex response period (4.33%) than during the simple response period (3.76%), $F(1,21) = 5.67$, $p=0.0268$. Variability of accelerator position also shows an interaction between code and stage, $F(1,21) = 7.23$, $p=0.0137$, as shown in Figure 5.9. The variability of accelerator position remains constant for spatial IVIS tasks. However, accelerator position variability during the verbal trials is greater than the baseline level during the perception stage and lower during the simple response stage. These results suggest that the verbal IVIS task interfered with the driving task, while the spatial IVIS task did not. These results conflict with the MRT predictions; however, they might be explained because the spatial information could be interpreted by the drivers in a relatively simple spatial map, whereas the verbal information could not.

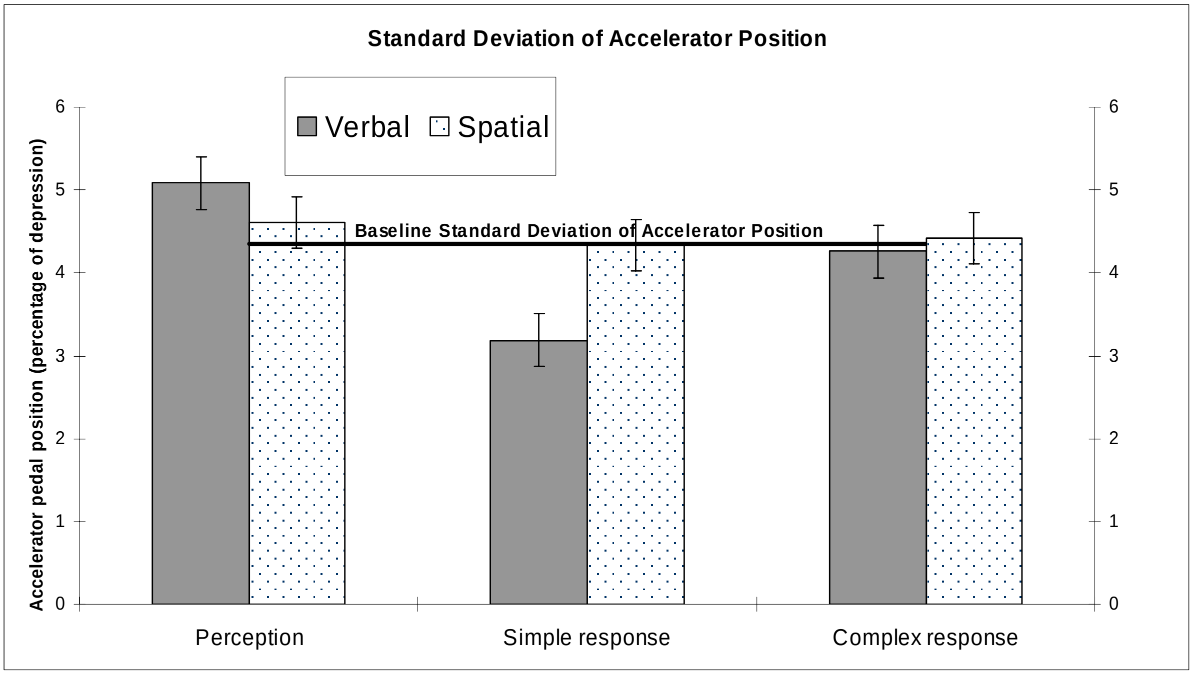


Figure 5.9. Effect of stage and code on standard deviation of accelerator position.

A measure of steering error was calculated using a second-order Taylor expansion and values of steering wheel position that had been averaged for a time period of 150 ms (Nakayama, Futami, Nakamura, & Boer, 1999a). The mean and standard deviation of the absolute value of the difference between the value predicted by the Taylor expansion and the actual value was calculated for the 15 seconds preceding a braking event. Mean steering error was less during the no IVIS baseline events compared to the spatial baseline, $t(41) = 7.30$, $p<0.0001$, and the verbal baseline, $t(41) = 6.39$, $p<0.0001$. The verbal baseline was not statistically different than the spatial baseline, $t(41) = 0.97$, $p=0.3386$. The standard deviation of steering error followed the same pattern, with significantly less variation during the no IVIS baseline drive events compared to the spatial events, $t(41) = 5.93$, $p<0.0001$, and the verbal events, $t(41) = 5.58$, $p<0.0001$. Again, the verbal and spatial baselines were not significantly different, $t(41) = 0.35$, $p=0.7282$.

Combining the mean steering error for the verbal and spatial baselines into an IVIS baseline and comparing this with the mean steering error for both the no IVIS baseline and the IVIS task reveals that the mean steering error during the no IVIS baseline drive was significantly less than that during the IVIS tasks, $t(41) = 7.41$, $p<0.0001$, and that during the IVIS baseline, $t(41) = 6.54$, $p<0.0001$. Mean steering error was not significantly different for the IVIS task and the IVIS baseline, $t(41) = 1.22$, $p=0.2294$. The standard deviation of steering error for the no IVIS baseline drive was significantly less than for the IVIS tasks $t(41) = 6.28$, $p<0.0001$, and for the IVIS baseline $t(41) = 5.86$, $p<0.0001$. Again, the IVIS task was not significantly different than the IVIS baseline, $t(41) = 0.55$ $p=0.5856$. Thus, steering error provides additional evidence that the effect of the IVIS interactions carried over to the periods between interactions. These results can be seen in Figure 5.10.

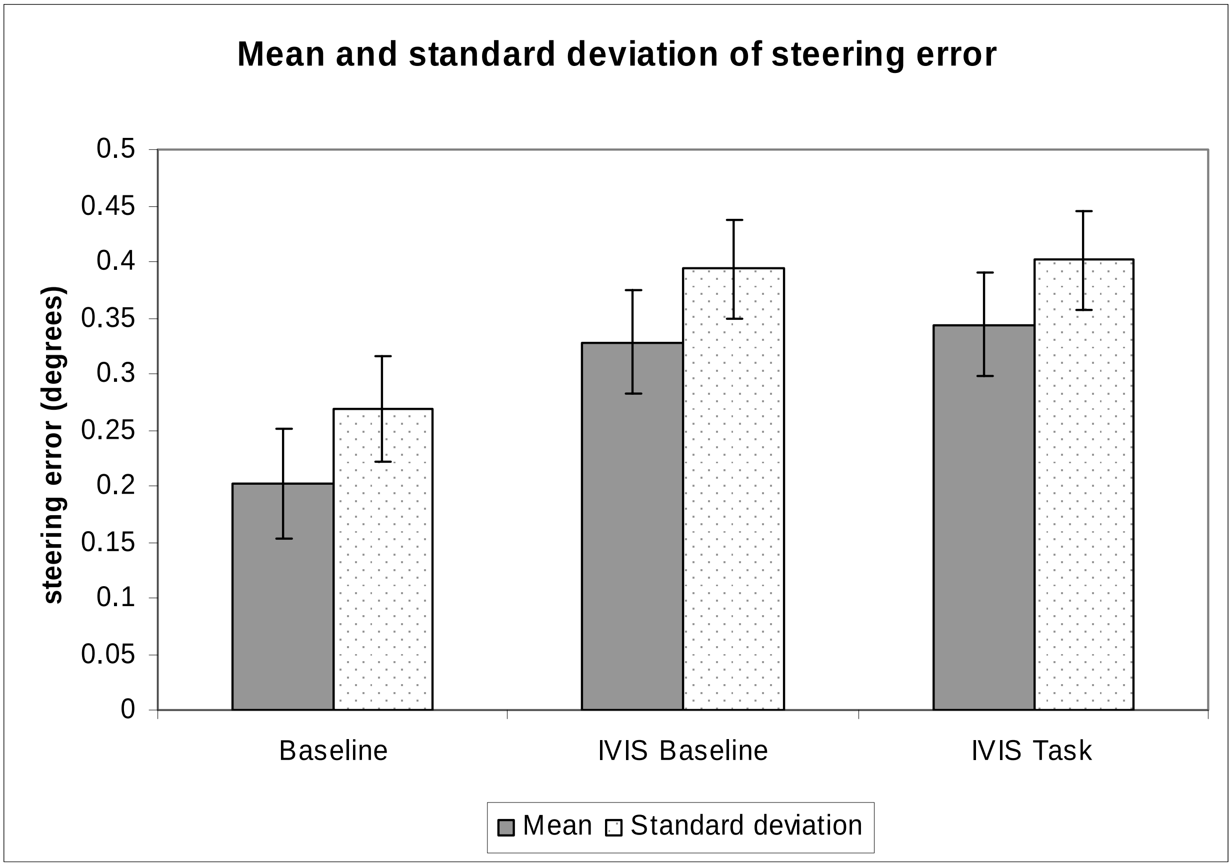


Figure 5.10. The effect of IVIS task on mean and standard deviation of steering error.

Steering wheel angle was used to calculate steering entropy (Nakayama et al., 1999a) for each drive. A SAS proc MIXED model containing only steering entropy (on an event-basis, with the entropy values based on the whole drive) shows that steering entropy had a significant effect on both brake reaction time, $F(1,775)=22.19$, $p<0.0001$, and accelerator release time, $F(1,761)=9.12$, $p<0.0026$. Another proc MIXED analysis reveals that task had a significant effect on steering entropy, $F(1,19)=33.40$, $p<0.0001$.

Each of the various measures of velocity and accelerator position reveals a significant effect of stage. Since the ordering of stage is fixed (perception always precedes response), the effect of stage on these dependent measures cannot be unambiguously linked to the cognitive load associated with a particular processing stage. However, this is not the case with the effect of response complexity. The level of complexity does affect driving performance, suggesting that responding to IVIS messages can distract drivers and that complex responses tend to be more distracting than simple responses.

5.4.2 Measures of driver distraction and IVIS interactions

A particularly promising set of measures of driver distraction can be developed from eye movements. Even for situations that involve no manual response or visual demand, cognitive load can influence eye movements in a systematic manner. To examine this possibility, the fixation duration, standard deviation of fixation duration, saccade distance, standard deviation of saccade distance, variance in visual scan area, and proportion of short fixations were analyzed in a manner similar to the driving performance variables. The average saccade distance and standard deviation in saccade distance were further reduced into vertical and horizontal components. This helped to better understand how the scan pattern was being affected by IVIS interaction. Variability in the above mentioned measures have been found to indicate levels of cognitive demand. An increase in fixation duration has been linked to a systematic increase in cognitive load (Recarte & Nunes, 2000; Strayer, Drews, & Johnston, 2003; Strayer & Johnston, 2001), and a decrease in saccade distance has been found to indicate increase in cognitive load (Recarte & Nunes, 2000). Finally, the proportion of fixations shorter than 250 ms (Boot & McCarley, in press) was calculated because it has been shown that high proportions of short fixations can be indicative of high levels of cognitive demand. The eye movement measures were calculated for a 15-second period immediately preceding the initiation of each lead vehicle braking event.

Eye movement measures were taken for the baseline periods described above. Unlike many of the driving performance measures, there were differences between the no IVIS baseline condition and the IVIS baseline conditions. The mean fixation duration and mean saccade distance were significantly different for all of the baselines. The mean fixation duration was 0.56 seconds for the no IVIS baseline, 0.41 seconds for the spatial baseline condition, and 0.56 seconds for the verbal baseline condition, $F(2,38)=3.44$, $p=0.042$. The mean saccade distance, the distance between consecutive saccades, was 2.30 degrees of visual angle for the no IVIS baseline, 2.77 degrees for the spatial baseline, and 2.60 degrees for the verbal baseline, $F(2,38)=4.05$, $p=0.026$. Similarly, the standard deviation of fixation duration was significantly different between the three types of baselines. The standard deviation of fixation duration was 0.60 seconds for the driving only baseline, 0.39 seconds for the spatial baseline, and 0.54 seconds for the verbal baseline, $F(2,38)=6.11$, $p=0.005$. The average horizontal and vertical components of fixation position were unaffected by the type of baseline condition, $F(2,38)=0.15$, $p=0.860$ and $F(2,38)=0.80$, $p=0.458$, respectively. The standard deviation of horizontal fixation position was not statistically different across baselines, $F(2,38)=2.20$, $p=0.125$; however, it was significantly different for vertical fixation position, $F(2,38)=3.83$, $p=0.031$. The proportion of short fixations was significantly different between the baseline conditions. The average proportion of short fixations was 0.64 for the no IVIS baseline, 0.69 for the spatial baseline, and 0.64 for the verbal baseline, $F(2,38)=6.11$, $p=0.005$. Together these results suggest that eye movements were more sensitive to the cognitive demands of IVIS interactions than the braking response to a periodically braking lead vehicle. These results also show an effect of IVIS interactions that persists beyond the immediate interaction with the IVIS, affecting the driver even after the IVIS interaction is complete.

Comparing the baseline data to that of the IVIS interactions shows that mean saccade distance, standard deviation in fixation duration, and the proportion of short fixations were affected by IVIS interactions. The mean distance between saccades was greater during IVIS interaction (2.64 degrees) compared to baseline driving (2.30 degrees), where baseline driving includes no IVIS baseline, spatial baseline, and verbal baseline driving $F(1,18)=6.08$, $p=0.024$. Also, the variation in the amount of time fixating on an object was decreased during IVIS interactions (0.477 seconds) compared to baseline driving (0.6049 seconds), $F(1,18)=4.32$, $p=0.050$. IVIS interaction also affected the proportion of short fixations by increasing the proportion value from 0.640 during baseline driving to 0.680 during IVIS interactions F(1,18)=5.99, *p*=0.025.

Interestingly, nearly every eye movement measure was affected only by stage. No other experimental conditions or interactions had a statistically significant effect on the eye movement data. Table 5.2 and Table 5.3 summarize these results.

Table 5.2. Proc MIXED results for average fixation duration

Factor			F Value	P Value
Stage	1	21	6.91	0.0157
CodeM	1	20	0.14	0.7081
Level(Stage)	1	21	0.45	0.5092
CodeM*Stage	1	20	1.34	0.2611
CodeM*Level(Stage)	1	20	0.02	0.8852

Table 5.3. Proc MIXED results for average saccade distance

Factor			F Value	P Value
Stage	1	21	6.82	0.0163
CodeM	1	20	0.46	0.5067
Level(Stage)	1	21	0.95	0.3415
CodeM*Stage	1	20	0.15	0.7047
CodeM*Level(Stage)	1	20	1.45	0.2425

The only eye measure that did not follow this pattern was the proportion of short fixations, shown in Figure 5.13, which was also sensitive to the code of the IVIS messages. As expected, fixation duration was affected by the stage of IVIS interaction. Fixation durations were greater while listening to IVIS messages (0.63 seconds) than while responding to IVIS messages (0.42 seconds), *F*(1,21)=6.91, *p*=0.016, as shown in *Figure 5.11*. In addition the variability of fixation duration was affected by IVIS stage. The standard deviation of fixation duration was greater while listening to IVIS messages (0.59 seconds) compared to IVIS message response (0.44 seconds), F(1,21)=4.64, p=0.043. Interestingly, neither the code of IVIS message (spatial or verbal) F(1,20)=0.14, p=0.708, nor the complexity of the response (simple or complex) F(1,21)=0.45, p=0.509, had an effect on fixation duration (see Figure 5.11).

Table 5.4. Proc MIXED results for proportion of short fixations

Factor			**F Value**	**P Value**
Stage	1	21	4.6	0.0438
CodeM	1	20	4.51	0.0464
Level(Stage)	1	21	2.21	0.1517
CodeM*Stage	1	20	2.72	0.1144
CodeM*Level(Stage)	1	20	0	0.995

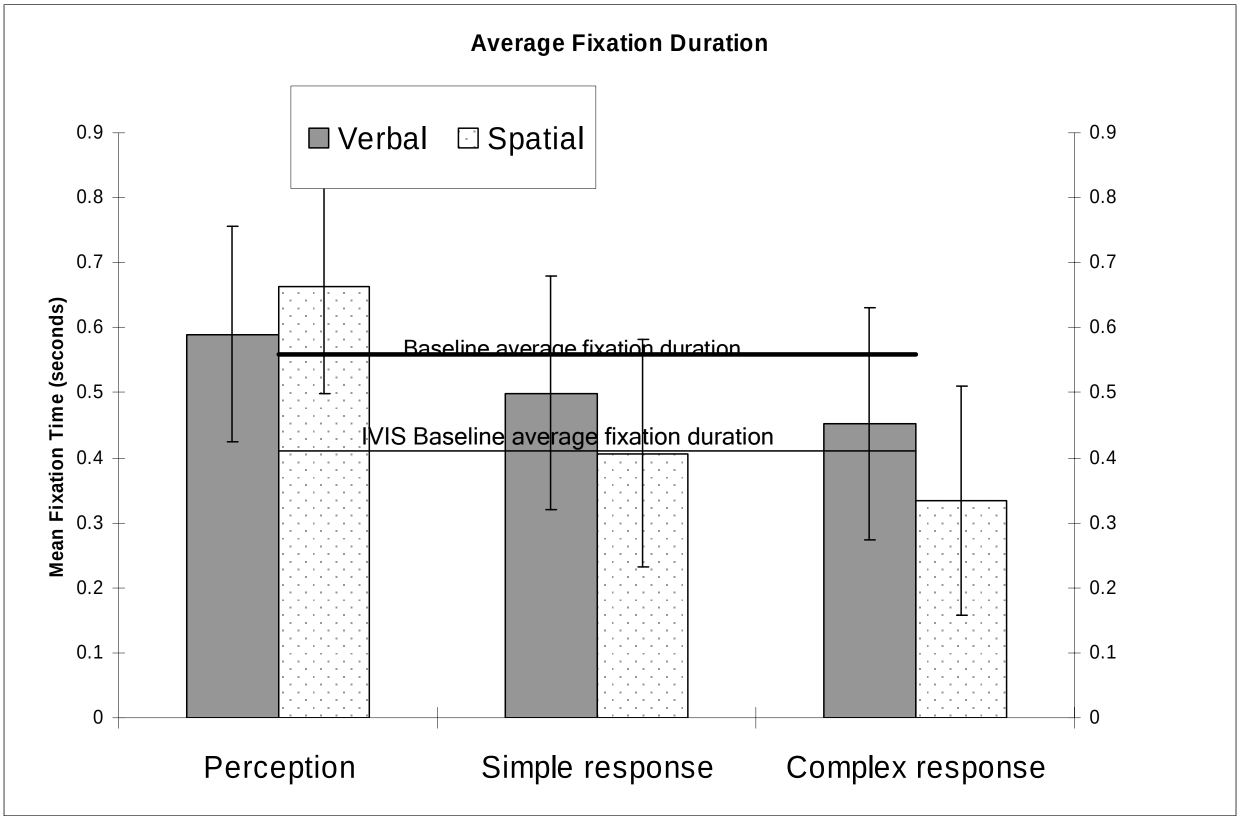


Figure 5.11. Effect of stage and code on average fixation duration.

Mean saccade distance was affected by the stage of IVIS interaction with saccade distance being shorter while listening (2.35 degrees) as compared to responding to an IVIS message (2.71 degrees), $F(1,21)=6.82$, $p=0.016$. Also, the variability in the distance traveled during saccades was affected by IVIS stage. The standard deviation of saccade distance was 2.20 degrees while listening and 2.66 degrees while responding, $F(1,21)=7.26$, $p=0.014$. The results indicate that the scan pattern during the response portion of IVIS interaction was more chaotic compared to the perceptual portion of the interaction. As with fixation duration, neither the code of IVIS message (spatial or verbal), $F(1,20)=0.46$, $p=0.507$, nor the complexity of the response task (simple or complex) $F(1,21)=2.21$, $p=0.152$, affected saccade distance. In addition, no significant interactions were found between the stage and the code of IVIS message, $F(1,20)=0.15$, p=0.705, nor response complexity, $F(1,20)=1.45$, p=0.243.

The standard deviations of the vertical and horizontal fixation position were multiplied, providing an estimate of the span of the drivers' eye movements. As shown in Figure 5.12, stage had a significant affect on the width of the area scanned. The area scanned while listening was 48.20 cm^2 compared to 70.65 cm^2 while responding, $F(1,21)=8.03$, $p=0.010$. A marginal interaction was found between response level and code, $F(1,21)=3.69$, $p=0.069$. The graph illustrates that scanning during response to verbal messages covered a greater area during complex responses than during simple responses. The opposite effect is seen for the spatial responses.

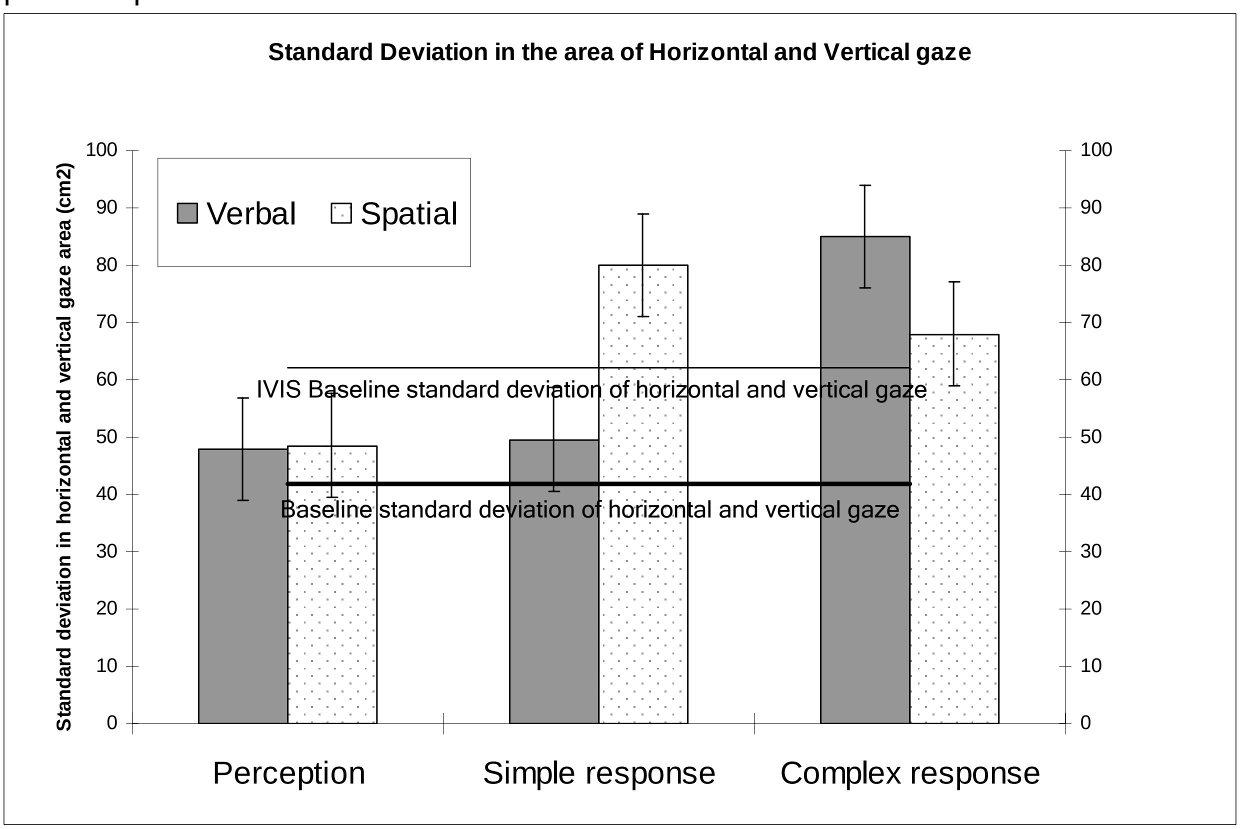


Figure 5.12. Effect of stage on the window size of visual scene scanned.

Although the variability of drivers gaze suggests a broader span of eye movements, these eye movements may not have been as effective in assimilating information, an issue addressed by the number of short fixations. Figure 5.13 shows the proportion of short fixations was affected by both stage and code during IVIS interaction, $F(1,21) = 4.6$, $p = 0.0438$, and $F(1,21) = 4.51$, $p = 0.0464$, respectively. The greatest proportion of short fixations occurred while responding (0.69) and the least occurred while listening (0.66), $F(1,21)=4.6$, $p=0.044$. In addition, a larger number of short fixations occurred during spatial IVIS interaction (0.70) compared to verbal IVIS interaction (0.66).

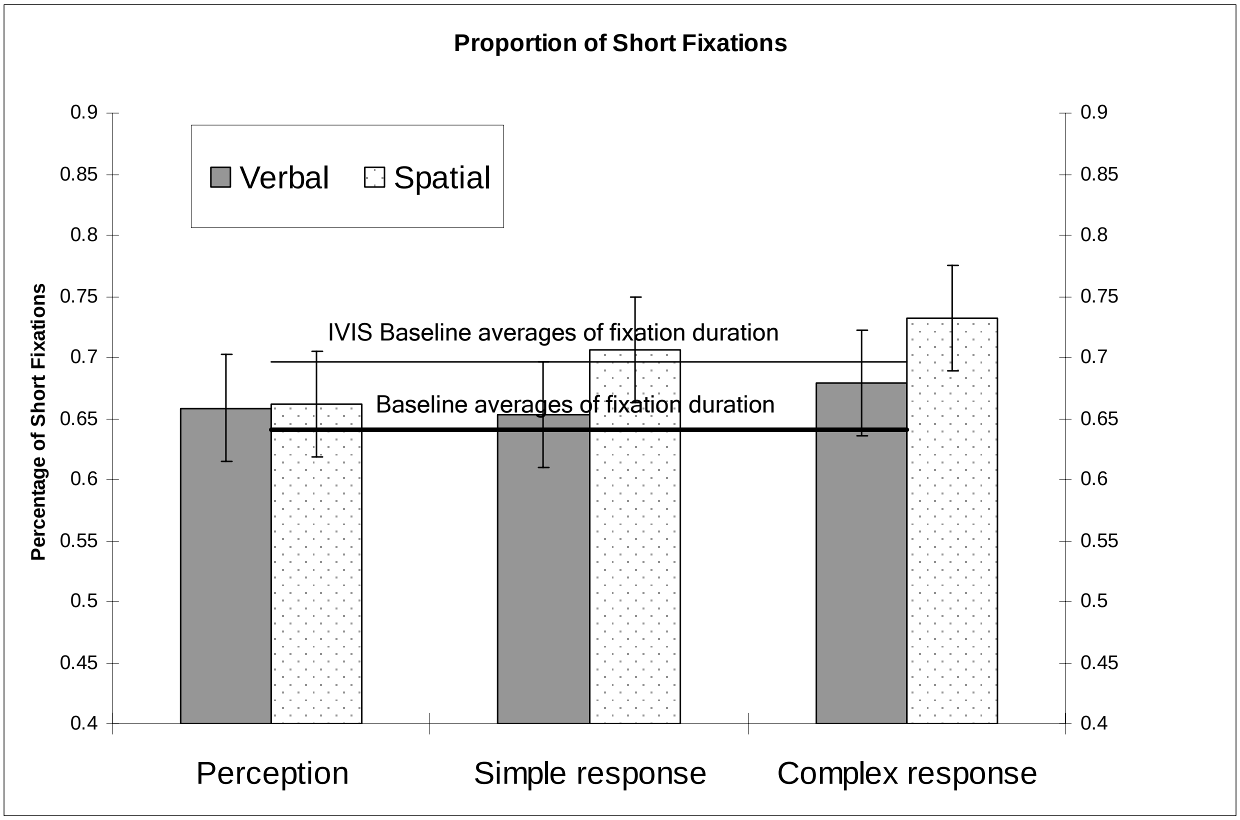


Figure 5.13. Proportion of short fixations, fixations less than 200 ms, by stage, code, and level.

It is clear that IVIS engagement had an effect on the driver's ability to scan the driving scene. Recarte and Nunes (2000) found that fixation duration increased when cognitively loaded. The current study found that as cognitive load increased fixation duration decreased. The decrease in fixation duration could be attributed to the message response decreasing the ability to effectively allocate attentional resources, thus reducing the search efficiency of the visual scene. A second eye measure affected during IVIS response was the saccade distance. As cognitive load increased during IVIS message response, the distance between successive fixations or saccade distance increased. A third measure affected during IVIS response was the proportion of short fixations. Recall that a large proportion of short fixations can be indicative of cognitive load (Boot & McCarley, in press). The current study found significantly higher proportion of short fixations during the response phase of interaction. The results indicate that during the response phase objects were fixated on for either a long or short period of time with the variability in area searched between object fixations increasing as compared to the perception phase.

All three of these results, in combination, help to explain a task switching occurring between the driving task and IVIS task. When participants are engaged in IVIS they may neglect the driving task causing a “freezing” effect in eye fixations increasing the overall duration. Following IVIS engagement, the driver may switch back to the driving task while quickly scanning the driving scene to gather visual information that may have been missed during IVIS engagement. This would create the increase in both search distance and proportion of short fixations observed in the current study. Previous studies have found a similar effect of fixations “freezing” while performing spatial imagery tasks during driving increasing the overall duration of fixations (Recarte & Nunes, 2000).

There are three possible reasons that effects opposite to those observed by Recarte & Nunes (2000) were seen for this study. The first is that the cognitive tasks used in the two studies were qualitatively different. A word generation verbal task and an imagery task involving the letters of the alphabet were used by Recarte and Nunes (2000) and each task lasted about 30 seconds. In this study, drivers had to remember a fair amount of information and reason from it in order to answer the IVIS questions. Each IVIS interaction lasted longer than 2.5 minutes. A second explanation could be that there is a systematic difference between a simulator environment and real world driving environment. The lack of depth perception in the simulated environment alter driver scan patterns. In addition, the simulator used for the current experiment contains one forward view screen with a 50 degree field of view. This could also have an effect on the scanning strategies. However, because participants do not have to scan as much total area of a driving scene compared to on road driving a large difference in the amount of scene scanned may even increase the significance of the finding. It should be easier to scan the visual scene in the simulated environment due to the reduction in field of view compared to on road driving. Finally, the quality of the eye movement data in this study was less than desirable. The mean confidence value (a performance indicator for the eye tracker) in the eye data in this report was 52%.

Previous studies of the effect of cognitive load on eye movements have focused on the relatively simple descriptive statistics just discussed. The differential effect of cognitive load on control and tactical braking tasks suggests measures that capture the time varying patterns of fixations may be sensitive to cognitive load. To address this issue, fixation patterns over several regions of interest (ROI) were investigated. First, the fixations were plotted using Matlab to examine the spread of the fixations over the visual scene. Then the boundaries of the ROIs were set according to the mean fixation location for each drive and the spread of the fixations. Then the percentage of total fixations appearing in each region was calculated. Then the region boundaries were adjusted to distribute the fixations across the regions of interest. Regions that contained a large fraction of the fixations were divided into smaller regions and some adjacent regions with few or no fixations were combined. From these investigations, two patterns of ROIs were selected, shown in Figure 5.14 and Figure 5.15. Transition matrices, which represent the probability of successive fixations transitioning from one region to another region, and probability matrices, which represent the probability of a fixation occurring in a specific region, were calculated for each drive and each IVIS experimental condition.

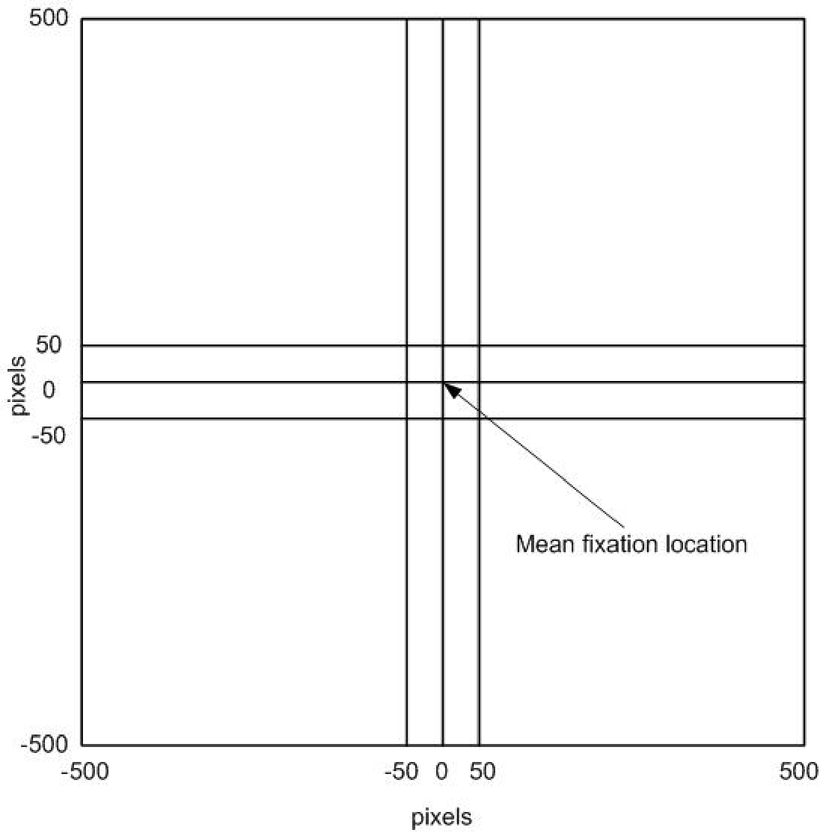


Figure 5.14. First pattern of regions of interest (ROI).

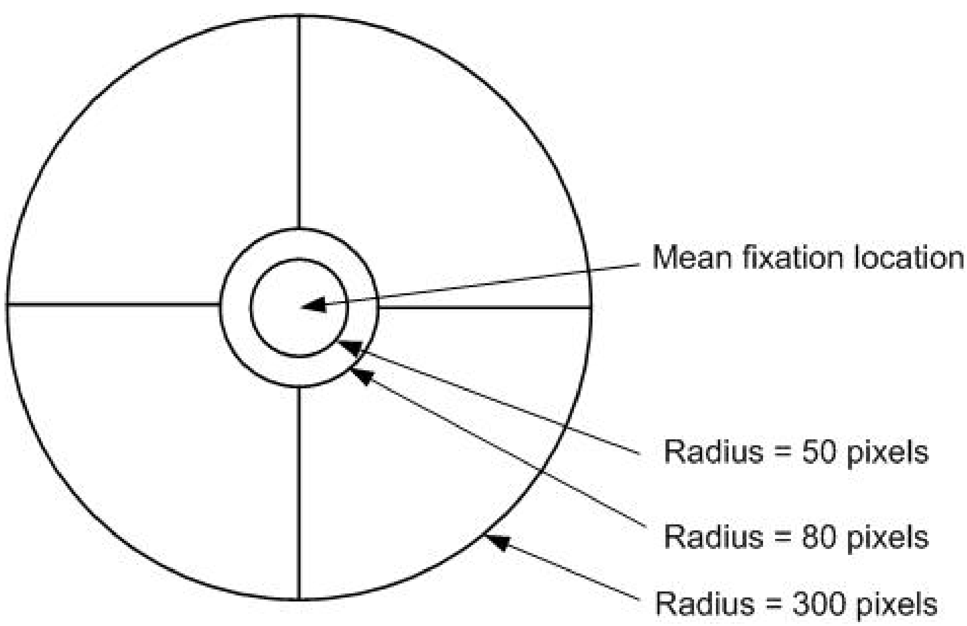
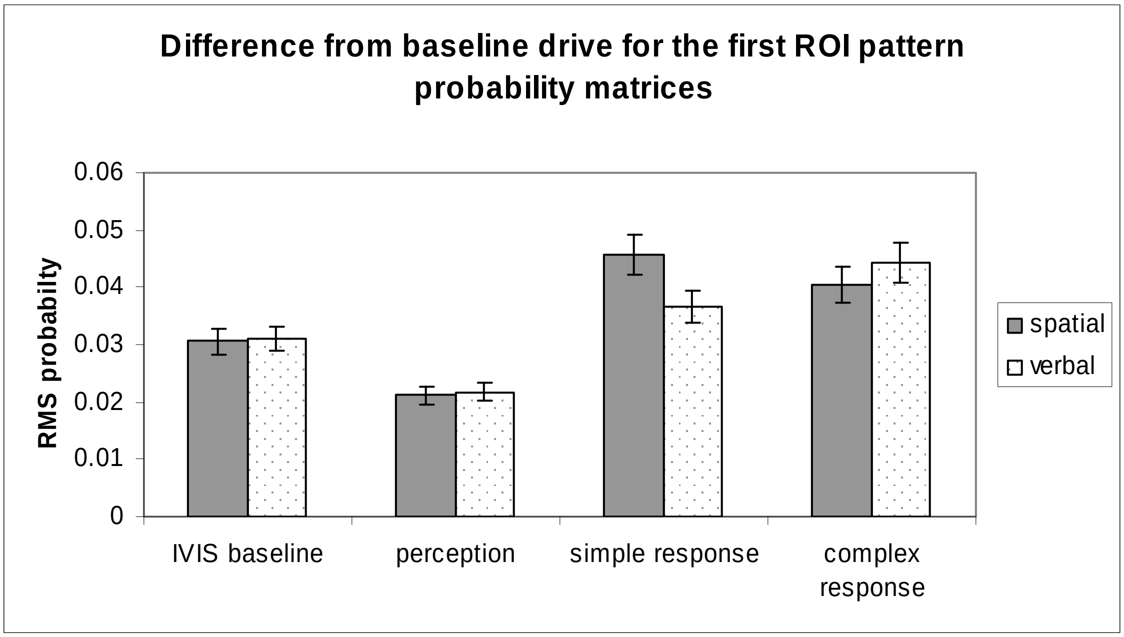


Figure 5.15. Second pattern of regions of interest (ROI).

Probability and transition matrices were analyzed by calculating the root mean square relative to the baseline drive. The probability and transmission matrices for each driver's no IVIS baseline drive were calculated. Then the difference between each matrix representing an experimental condition for a specific experimental drive (e.g., the perception matrix) and the no IVIS baseline drive was squared and these squared differences were summed for all cells. The final step was to take the square root of this average. These totals are show in Figure 5.16 and Figure 5.17.



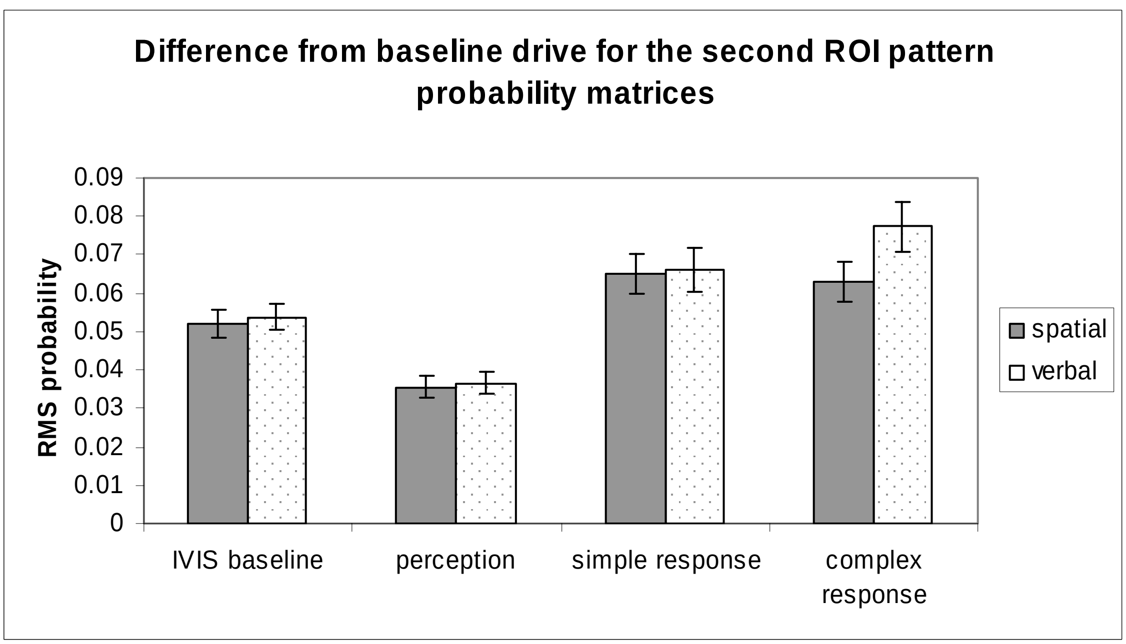
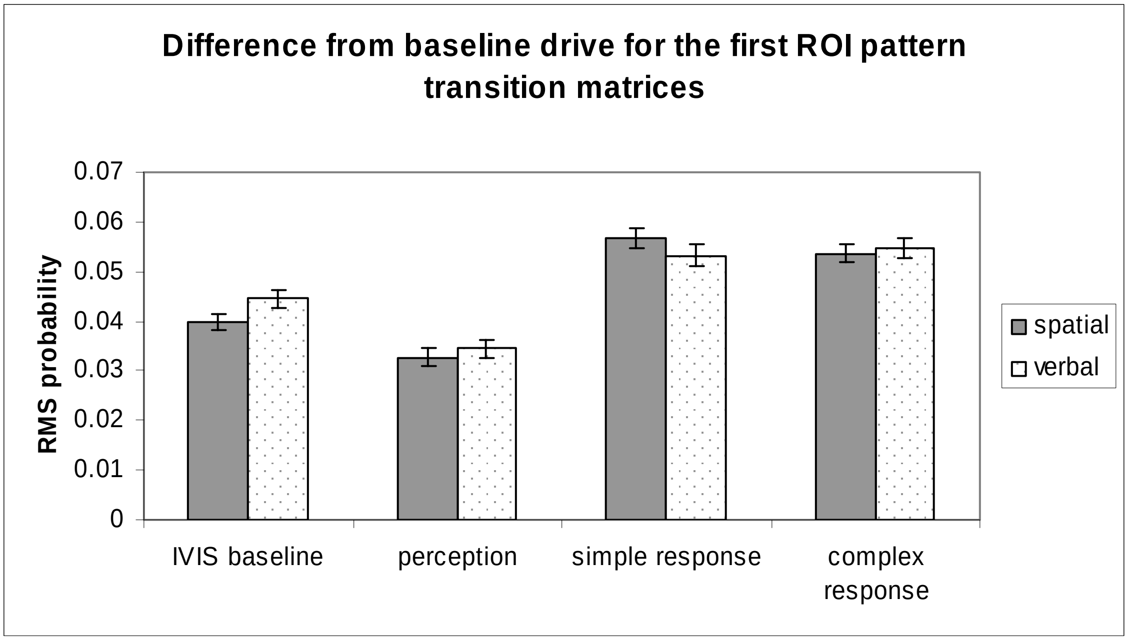


Figure 5.16. The rms differences from the baseline drive for probability matrices for the two patterns of regions of interest.



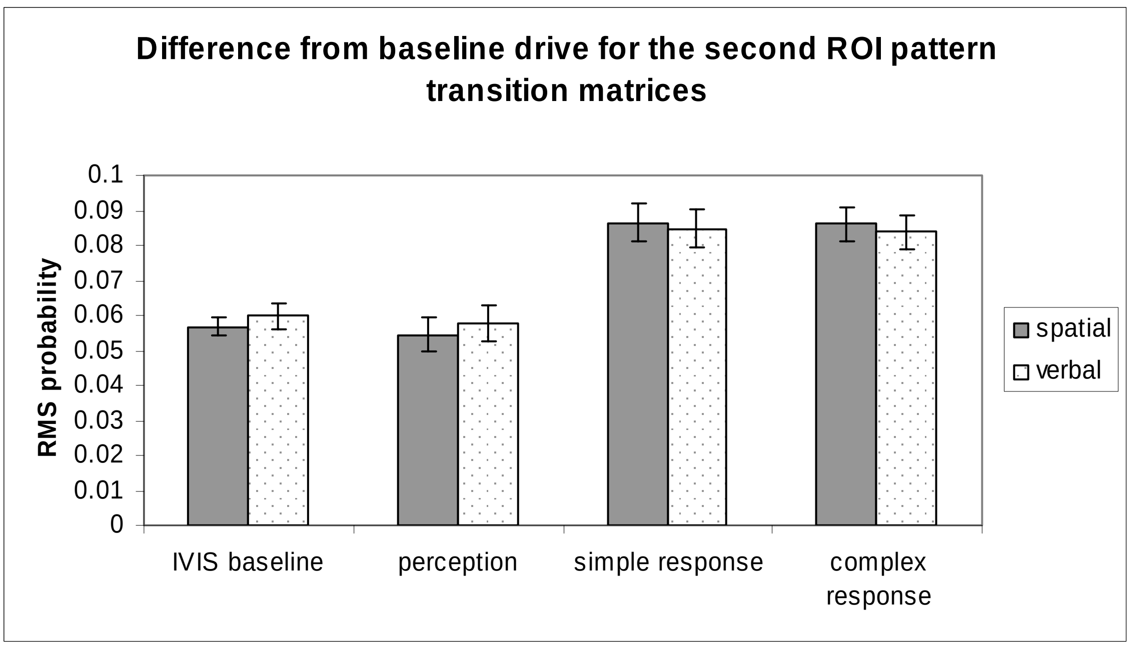


Figure 5.17. The rms differences from the baseline drive for transition matrices for the two patterns of regions of interest.

As the rms differences for the both the probability and transition matrices show, for both patterns of ROIs, the distribution and movement of fixations across the ROIs are least different from the no IVIS baseline drive for the perception condition. As expected, the distribution and movement of fixations across the ROIs are most different from the no IVIS baseline drive for the response condition. These results support the hypothesis that listening to IVIS information affects eye movements differently than responding to the IVIS questions. Even though the rms differences were not sensitive to response complexity and for the most part, verbal rms differences were not different that spatial rms differences, there is clear evidence that eye movement data was sensitive to IVIS engagement.

5.4.3 Heart rate variability and driver distraction

The mid-range frequencies (0.07-0.14 Hz) of cardiac rhythms are indicative of mental effort (De Waard, 1996). Electrocardiogram data were analyzed using BIOPAC Systems, Inc.'s AcqKnowledge software to calculate the power in the 0.1 Hz frequency range. First, a method consisting of correlating, filtering, and peak finding was used to find the inter-beat interval (IBI). This data was manually inspected and artifacts were removed. Matlab software (Version 6.5.0) was used to calculate the power of the 0.07 to 0.14 Hz range. The *interpl* function was used to linearly interpolate and sample the IBI data at 4 Hz. The SPECTRUM function was used to calculate the power spectral density in the frequency range of interest for each drive. This particular function utilized Welch's method with Hanning windows of length 2048 which overlapped by 50%. The results from this analysis were output in units of milliseconds squared (ms^2).

Because heart rate variability was calculated on a per drive basis, the value for each drive was applied to each event in that drive. Both accelerator release and brake reaction times were affected by 0.1 Hz frequency range of the heart rate data, $F(1,602) = 4.62$, $p=0.0011$, and $F(1,602) = 16.61$, $p=0.0321$, respectively. However, when the 0.1 Hz frequency was analyzed on a per drive basis it was found that this measure was not indicative of whether or not the driver was performing the IVIS task during the drive, $F(1,17) = 1.99$, $p = 0.1765$.

5.4.4 The predictive ability of the measures of driver distraction

The ultimate purpose of this experiment was to identify promising driver state variables and ways of combining those variables to predict the driving performance decrements. Comparison of braking response and other driving performance measures showed that the IVIS interactions had a modest effect on driving performance. The IVIS interactions also had a modest but consistent effect on many of the eye movement variables. This section evaluates whether the eye movement data can be combined to predict driving performance decrements.

As a first step in this process, a factor analysis (SAS proc factor) was used to investigate the interrelationships among the variables describing eye movements in the 15 seconds before each braking event. The analysis revealed two groups of eye movement variables. The first factor correlates highly with standard deviation of saccade length (r = 0.926), mean saccade length (r = 0.919), standard deviation of horizontal fixation position (r = 0.875), standard deviation of saccade (r = 0.782), mean saccade speed (r = 0.753), and standard deviation of vertical fixation position (r = 0.500). This first factor seems to reflect overall spatial variability in eye movements. The second factor correlates highly with both the mean (r = 0.880) and standard deviation of fixation duration (r = 0.885). The second factor also varies inversely with proportion of short fixations (r = -0.823). This factor may reflect the efficiency of information extraction associated with each fixation. A large number of short fixations and highly variable fixation durations may indicate inefficient information assimilation.

A linear regression model was developed using these factors. Using SAS proc GLM, a linear regression model used the factor scores associated with the two factors to predict accelerator release reaction time and brake reaction time. For accelerator release reaction time, the factor associated with the spatial variability of the fixation location had statistically significant association, $F(1,785)=7.94$, $p=0.0049$. The second factor showed only a marginally significant influence, $F(1,785)=2.75$, $p=0.0977$. Together these two factors explain a small proportion of the variance in the driver's accelerator release reaction time, 1.3%. Using these two factors to predict brake reaction time shows a substantially stronger association between the first factor and the brake reaction time, $F(1,785)=35.06$, $p=0.0001$. The second factor shows no association, $F(1,785)=.49$, $p=0.483$. The ability of the first factor to predict brake reaction time is limited, accounting for only 3.7% of the variance of reaction time. The factor scores used in these models reflect the correlations among the measures of eye movements and this correlation structure may not be related to distraction and may not represent the best predictors of driving performance.

To evaluate the possibility that the individual dependent measures that characterize the eye movements may be better predictors than the factor scores a series of multiple linear regression models were developed. A preliminary model was constructed that included all of the dependent variables associated with the eye movements, such as the mean fixation duration, mean horizontal position, and mean saccade distance. Several of these dependent measures were significant at 0.05 level. Variables that did not provide a significant contribution to the prediction of reaction time were eliminated from the model. This procedure was repeated until a model composed of mean fixation duration, mean horizontal position, the mean saccade speed, proportion of short fixations emerged to predict the accelerator release reaction time. As shown in Table 5. 5, this model fit the data slightly better than that composed of the factor scores, but still accounted for only 4.9% of the variance of the accelerator release reaction times.

Table 5. 5 Components of the linear regression model to predict accelerator release reaction time.

Predictor			**F Value**	**P Value**
Fixation duration	1	825	15.05	0.0001
Horizontal position	1	825	20.42	<0.0001
Saccade speed	1	825	8.25	0.0042
Proportion of short fixations	1	825	10.54	0.0012

Table 5. 6 Components of the linear regression model to predict brake reaction time.

Predictor			**F Value**	**P Value**
Horizontal position	1	825	5.48	0.0194
Standard deviation of vertical position	1	825	13.03	0.0003
Saccade speed	1	825	15.00	0.0001

The model for the brake reaction time includes a different set of predictors. Like accelerator release reaction time, brake reaction time depends on the mean horizontal position and the mean saccade speed. Unlike the accelerator release reaction time, the brake reaction time does not depend on the proportion of short fixations. It does, however, depend on the standard deviation of the vertical position. Like the predictions of the accelerator release reaction time, the model accounts for only a 4.8 % of the variance in the brake reaction time.

The results from the factor analysis and the linear regression models reveal some interesting patterns that may have important consequences for understanding the effect of cognitive demands on driving performance. The factor analysis suggests eye movement parameters reflect two underlying dimensions. The first dimension reflects the spatial variability of fixations and the second reflects the temporal variability of fixations. These dimensions are consistent with previous research associated with the efficient distribution of visual attention (spatial variability) and the efficient assimilation of information (temporal variability). Both of these dimensions are slightly related to driver performance in responding to a braking lead vehicle. Both the spatial and temporal variability contribute to the prediction drivers' initial response to the lead vehicle behavior but only the spatial variability predicts the subsequent time to apply the brake. This general pattern is confirmed with the linear regression models based on the individual eye movement parameters. Proportion of short fixations, a variable related to the temporal variability of fixations was strongly associated with the accelerator release reaction time, but not the brake reaction time.

The linear regression models, together with the analysis of the effect of the various IVIS tasks on the various eye movement parameters suggests that the eye movement parameters are sensitive to different types of cognitive load and that these types of cognitive load affect driver response differently. The cognitive load that affects the temporal variability of eye movements affects the initial response, whereas the cognitive demands that affect the spatial variability affect the subsequent braking response. Specifically, these results suggest that the temporal variability component of eye movements would be particularly sensitive to detecting decrements in tactical driving performance, such as the response to emerging conflict situations, whereas the spatial variability component of eye movements might better predict driving control performance, such as the impending collision with a vehicle braking lead vehicle.

5.4.5 Hidden Markov Models

Hidden Markov models (HMMs), proposed by Baum and his colleagues in the 1960's (Baum, 1972; Baum & Egon, 1967; Baum & Petrie, 1966; Baum, Petrie, Soules, & Weiss, 1970; Baum & Sell, 1968), represent stochastic sequences as Markov chains where the states are not directly observed but are associated with a probability density function (Rabiner & Juang, 1986). HMMs are a doubly stochastic process where the underlying stochastic process is not directly observed but can be exposed through another set of stochastic processes that produce a sequence of observed symbols or emissions (Rabiner, 1989; Rabiner & Juang, 1986). HMMs are used to build a signal model that explains and characterizes the occurrence of observed signal outputs. In order to build the model, two pieces of information are required. The first is the transmission matrix, which represents the probability of the system moving from any one state to any other state or of remaining in the same state. The second is the emission matrix, which represents the probability of a given emission while the system is in a given state. With this information, a model can then process the signal output patterns of other sequences in order to predict system state.

HMM algorithms were applied to the eye movement data in various ways. Three aspects of application which were modified included:

- emission sequence (ROIs from Pattern 1 or Pattern 2, or saccade distance)
- level of data aggregation (none, or 5, 10, or 15 seconds)
- number of IVIS states included in the model (2-state or 3-state).

Two different categories of emissions were analyzed. The first type was which region of interest the fixation occurred in. This type of emission was analyzed for both patterns of ROIs, presented in Figure 5.14 and Figure 5.15. The second type of emission analyzed was the length of the saccade distance, which was divided into seven different ranges.

Three different levels of data aggregation were attempted. It was thought that HMM might be more effective at predicting IVIS state if more data were considered at each timestep. Data were averaged over lengths of 5, 10, and 15 seconds.

Finally, neural network analysis was used to determine the best number of states to represent driver distraction because research has shown that results from neural network analysis increase the classification accuracy and reduces the classification time of the Markov model (Salah, Alpaydm, & Akarun, 2002). The analysis determined that system state was best modeled with two states (IVIS interaction and no IVIS interaction). Thus, the analysis focused mainly on 2-state HMMs, but a few 3-state HMMs (no IVIS interaction, perception, and response) were also included.

HMM functions from Matlab's Statistics Toolbox 4.1 were used to investigate the ability of HMMs to predict IVIS state. The experimental protocol called for two verbal and two spatial experimental drives for each driver. The two verbal drives for each driver were paired, as were the two spatial drives. Then one of the drives from each set was used to calculate the transmission and emission matrices. Then these matrices were used to build a HMM that could predict the mostly likely IVIS state given the sequence of emissions for the second drive. The likely states were compared with the actual system states to calculate the HMM performance.

Performance was analyzed in the following way. For each HMM a matrix was created. The columns of the matrix represented the actual system states while the rows represented the predicted system states. A model with good performance would have a large number of observations in the cells along the main diagonal and have relatively few observations in the other cells. Chi-square values were calculated for each cell and then totaled for each matrix.

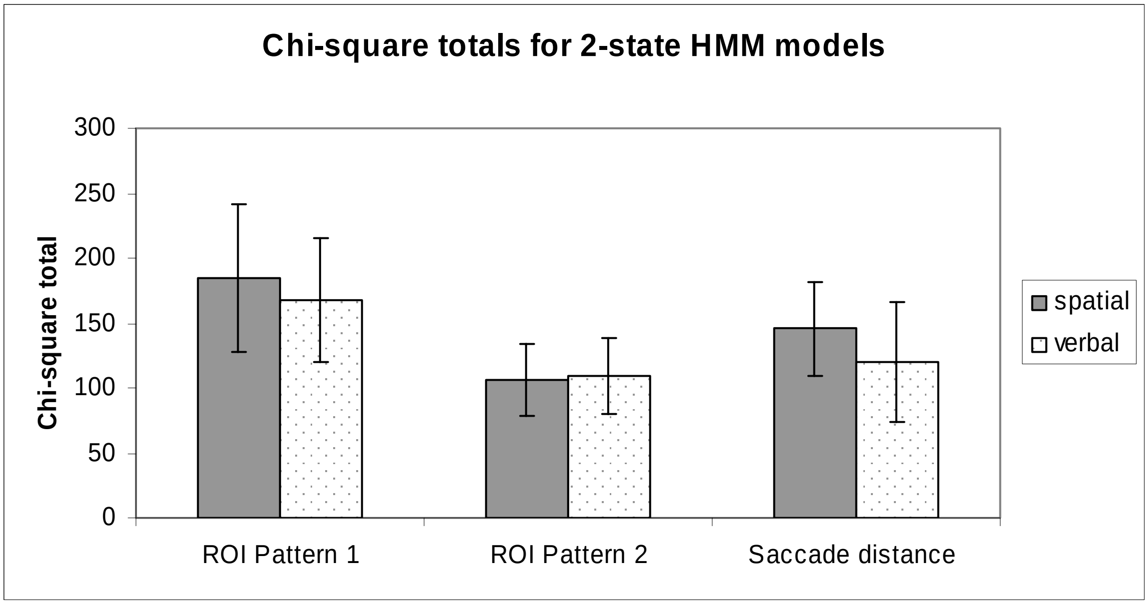


Figure 5.18. Chi-square totals for 2-state HMMs.

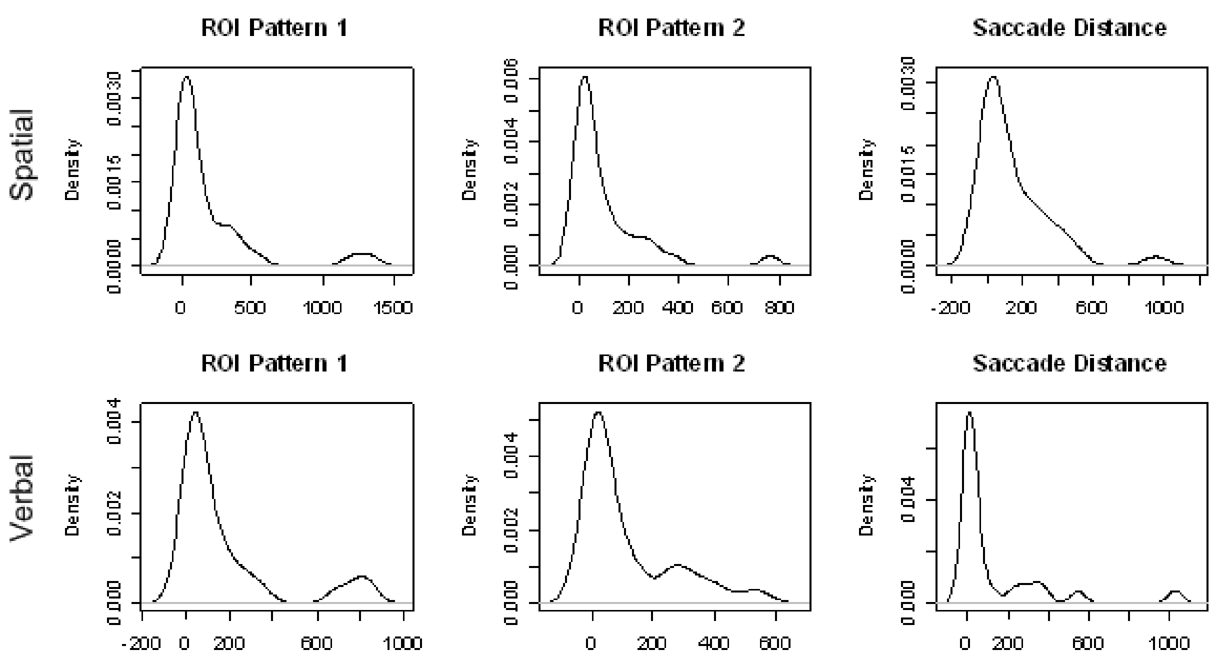
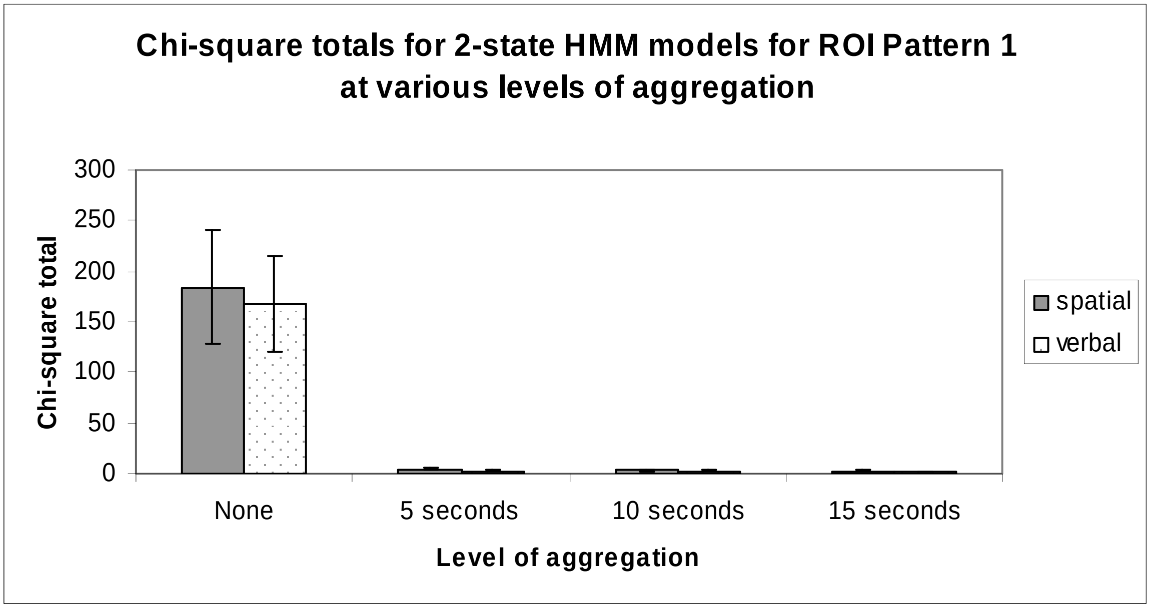


Figure 5.19. Distributions of chi-square values for three different emissions for 2-state HMMs.

As Figure 5.18 shows, the HMMs for all three kinds of emissions performed at approximately the same level and no significant differences were seen between spatial and verbal performance. The performance of each HMM for each drive varied a great deal as shown in Figure 5.19. The distributions of the chi-square values are heavily skewed to the right, meaning that for each model performed very well for a few drives. The distributions also show that the HMMs performed poorly for many drives.



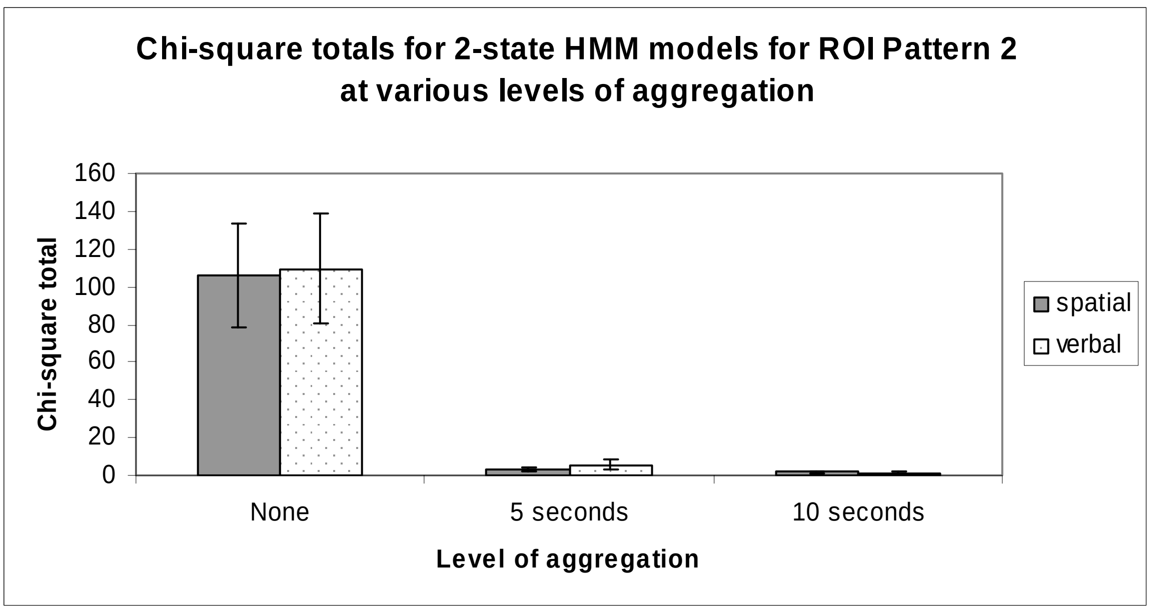


Figure 5.20. Chi-square totals for 2-state HMMs for ROI Patterns 1 and 2 with aggregated data.

As the graphs in Figure 5.20 show, the HMMs for all levels of aggregation performed very poorly when compared to no aggregation. This likely occurred for two reasons. Aggregation decreased the number of observations present in each cell of the performance matrix. The chi-square total is based on the square of absolute difference between the number of expected and actual observation. Therefore, decreasing the number of observations by a factor of 10 reduces chi-square values by a factor of 10. However, this effect does not account completely for the drastic difference in chi-square values seen for the aggregated data HMMs. Aggregating the data further reduced the number of timesteps during which the system was in a no IVIS state. With fewer of these transitions in the sequence used to set the model parameters, the HMMs were very unlikely to ever predict a no IVIS state. Thus, the cells in the performance matrix row corresponding to state prediction of no IVIS often contained no observations. When this occurred, the zero value was changed to 1 because chi-square analysis depends on there being at least one observation in each cell. The graphs in Figure 5.20 show that, at least in this particular case, aggregation of the data was not helpful.

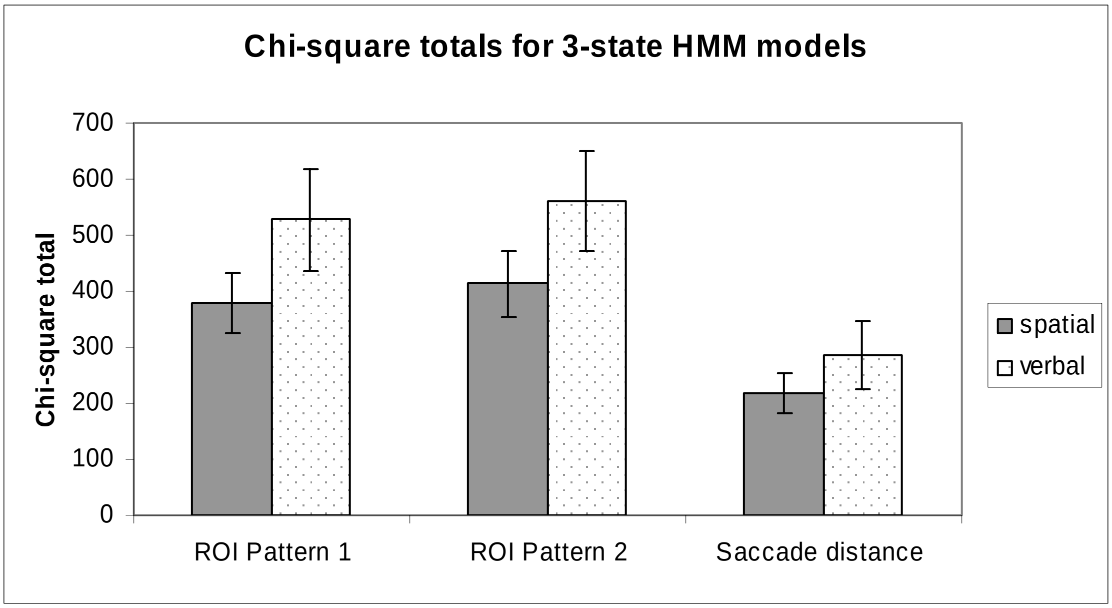


Figure 5.21. Chi-square totals for 3-state HMM models.

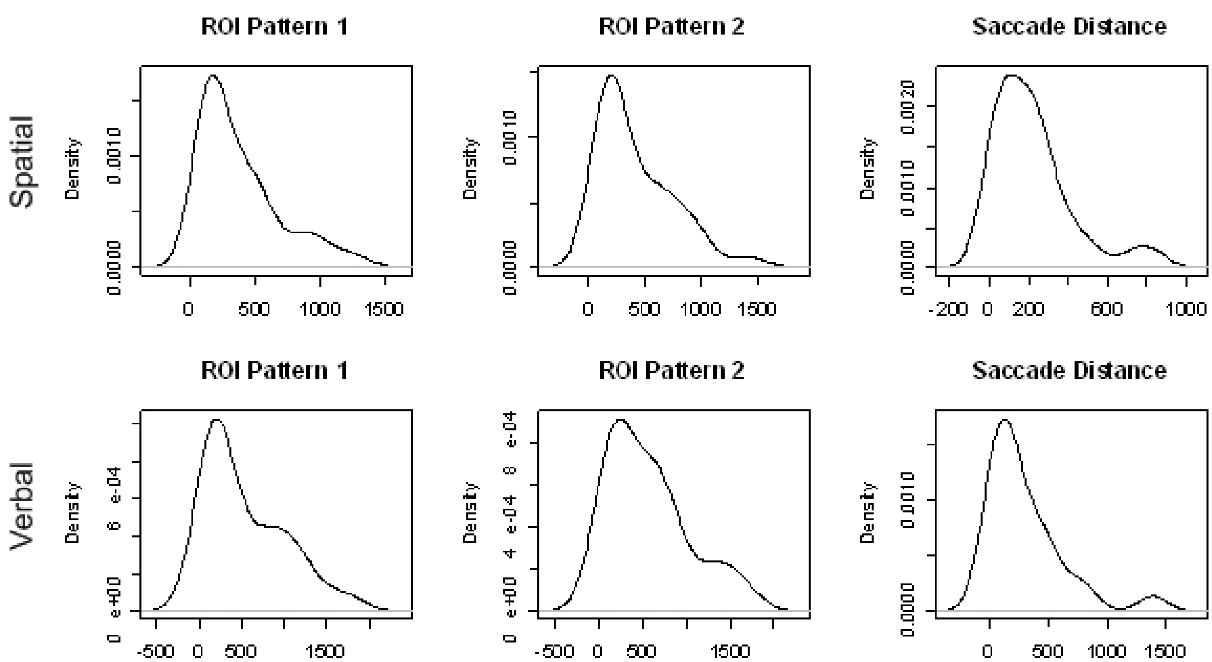


Figure 5.22. Distribution of chi-square values for three different emissions for 3-stage HMMs.

Finally, chi-square values were calculated for 3-state models for each type of emission. The results in Figure 5.21 show that the HMMs which included ROIs as the emission sequence performed better than those which included saccade distance. The distributions of the chi-square values are again very much skewed to the right and a large number of values are small meaning that, just as for the 2-state HMMs, each model performed very well for a few drives and badly for many drives.

Overall the results of this HMM analysis suggest that for the current state of understanding about the HMMs and their relationship to the eye movement data and the IVIS interactions, HMMs alone may not be suitable for detecting driver distraction. However, given the high performance of each HMM for a few drives and the moderate performance of each HMM for several more drives, there is some evidence that with further understanding and investigation HMMs can predict distraction based on eye movement data. Some possible areas of future investigation in this particular application of HMMs include:

- Investigation of other emission variables. There are an infinite number of possible ROI patterns, but only two were discussed here. Similiarly, there are mainly other eye movement measures other than saccade distance. The difference in performance for the 3-state models shown in Figure 5.21 support the conclusion that a particular emission variable may not perform well in different HMMs.
- Combinations of HMMs working in tandem. Each HMM can only consider one emission sequence. This is a problem because distraction may be best indicated by a combination of measures. One solution to this problem is to consider several HMMs working simultaneously, each monitoring an individual variable, and then pooling the predictions of each HMM to create a final prediction.

The finding that aggregating the eye data to create the HMM emission sequence failed drastically suggests that it may be possible detect driver distraction on a timeframe on the order of seconds rather than minutes. Finally, HMMs are only one type of model. As with all models, HMMs have limitations. Other computational models are currently being considered for the prediction of distraction as a part of Phase 2.

5.5 CONCLUSIONS AND PHASE 2 PLANS

5.5.1 General conclusions

The first objective of this experiment was to examine the driving performance decrements associated with different types of cognitive demands. Wickens' multiple resource theory and Pasher's information processing bottleneck theory were used to define theoretically relevant types of cognitive load. These types of cognitive load included IVIS interactions that imposed verbal and spatial demands at the perceptual and the response stages of processing. These types of cognitive load were evaluated in the context of a periodically braking lead vehicle. Some braking events could be anticipated and so demanded tactical driving performance. Others events could not be anticipated and so driver response depended on control driving performance. Consistent with Pashler's bottleneck theory, the results showed that the response stage of the IVIS interaction was more demanding than the perceptual stage. Listening to IVIS information is less demanding than responding to questions about it. The results also show that IVIS interactions degrade tactical driving performance more than control driving performance. IVIS interactions degrade a driver's ability to anticipate emerging conflict situations more than they degrade driver response to a conflict situation. Contrary to expectations, the spatial task, which involved information about the location of restaurants, did not degrade driving performance more than the verbal task, which involved price and quality information for restaurants. This may reflect the ease with which drivers could use a spatial map to code and respond to the spatial information. This efficient coding strategy may have made the spatial task less demanding than the verbal task, even though the spatial task competed for the same resources as driving. The difference in cognitive load between strategies may have had a greater effect than the difference in resource conflict associated with the task. Consistent with other studies, responding to IVIS information had a greater effect on driving performance than did listening to IVIS information. Overall, the results show that responding to IVIS messages degraded driving performance, particularly the ability to anticipate conflict situations.

The effects of the IVIS interaction on driving performance were modest and may reflect substantial individual differences and strategic adaptation, such as speed reduction. A slower speed places the lead vehicle closer to the driver when it begins to decelerate. This makes for a more salient braking event and potentially shorter response times. This adds to the variability of the data and undermines any systematic effect of the IVIS task demands.

The second objective of the experiment was to examine the relationship between IVIS demand and potential driver state variables. This analysis focused on eye movement variables but also considered heart rate variability. The eye movement variables showed promise as indicators of driver distraction. Overall the eye movement variables are particularly sensitive to the difference between the perceptual and response stages of processing. The eye movement variables also suggest an effect of the IVIS interaction that persists after the interaction is complete.

The third objective of this experiment was to predict distraction-related decrements in driver performance using driver state variables. Overall, the driver state variables associated with the eye movements predicted driver reaction time to a periodically braking the lead vehicle quite poorly, accounting for less than 5% of the variance in the accelerator release reaction time and brake reaction time. One explanation for this result is that the eye movements are not strongly linked to the cognitive demands of the IVIS tasks; however, a systematic influence of IVIS interactions on eye movements suggests this is not the case. A second explanation is that the reaction time measures are not strongly linked to the distraction of the driver. The relatively weak effects of the IVIS interaction on driver performance suggest the second explanation accounts for why the driver state variables are such weak predictors of driver performance. In addition, the predictions used only a simple linear model. More complex relationships may govern this relationship. Markov analysis, support vector machines, and neural net analyses are being used to further mine the data and investigate the potential for time-varying patterns and non-linear relationships to predict driver performance more precisely.

Hidden Markov Models were used to predict driver distraction from eye data with limited success. While greater understanding of the relationships between the eye data and the distraction state through further investigation of HMMs may improve performance, other models to predict distraction should also be investigated.

5.5.2 Implications for guidelines

These results suggest that assessing cognitive demand and its interaction with driving tasks requires a multi-dimensional approach. The differential effect of cognitive load on tactical and control braking events demonstrates that different driving tasks will be differently affected by cognitive load. Likewise, the analysis of the eye movement data suggests that groups of driver state variables predict different elements of driver performance.

This experiment also shows that the predictive ability of driver state variables is limited. Any mitigation strategy must be designed so that it is robust to poor predictions of distraction. The weak effect of the experimental conditions on drivers' braking performance suggests that substantial variability in drivers' braking response depended not only on the degree of distraction but also on differences in the drivers' individual safety margins and the interaction between the experimental conditions and strategic adaptation to the task demands, such as reducing the speed during the IVIS interaction. More detailed analyses and further experiments are needed to examine how drivers' strategic adaptation to various distractions interact with the driver state variables and how these adaptations affect response to various driving demands, such as merging, response to traffic signals, pedestrians, and curve negotiation.

5.5.3 Implications for Phase 2 activities

The primary focus of Phase 2 will be the development, validation, and implementation of algorithms that can precisely predict degrees and types of cognitive distraction. Task 5a defined a basic framework that describes the multiple types of distraction and their interaction. Phase 2 activities will build on this basic framework to improve the precision of distraction estimates and define the limits of distraction measurement techniques. Specific issues considered in Phase 2 include:

- Explore and assess the utility of various data interpretation techniques. Currently we are considering linear regression, support vector machines, and hidden markov models. These will be evaluated and others will be considered
- The strong effect of tactical and control braking events suggests these distinctions may be critical for in assessing driver distraction. The next phase of this work will examine how to create conflict matrices to predict decrements in tactical and control driving performance as a function of different tasks.
- Refine the measures used to predict distraction. Phase 1 identified measures that predict distraction and Phase 2 will identify what combination of variables provides the most timely and robust prediction.
- The dynamics of distraction are critical and so an experiment addressing workload transition will be conducted. This will serve to validate measures and to identify how the dynamics of distraction need to be considered.
- The refinement of measures and algorithms will address the requirements for real time implementation and guidance of adaptive mitigation strategies. A specific element of this is the degree to which distraction assessment depends on the time window of data.
- In an attempt to develop distraction measures with a high degree of timeliness we will investigate whether short time sequences of several variables provide a clear signal of distraction or disengagement from driving.

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