SAVE-IT

SAfety VEhicles using adaptive Interface Technology (Task 5)

A Literature Review of Cognitive Distraction

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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.

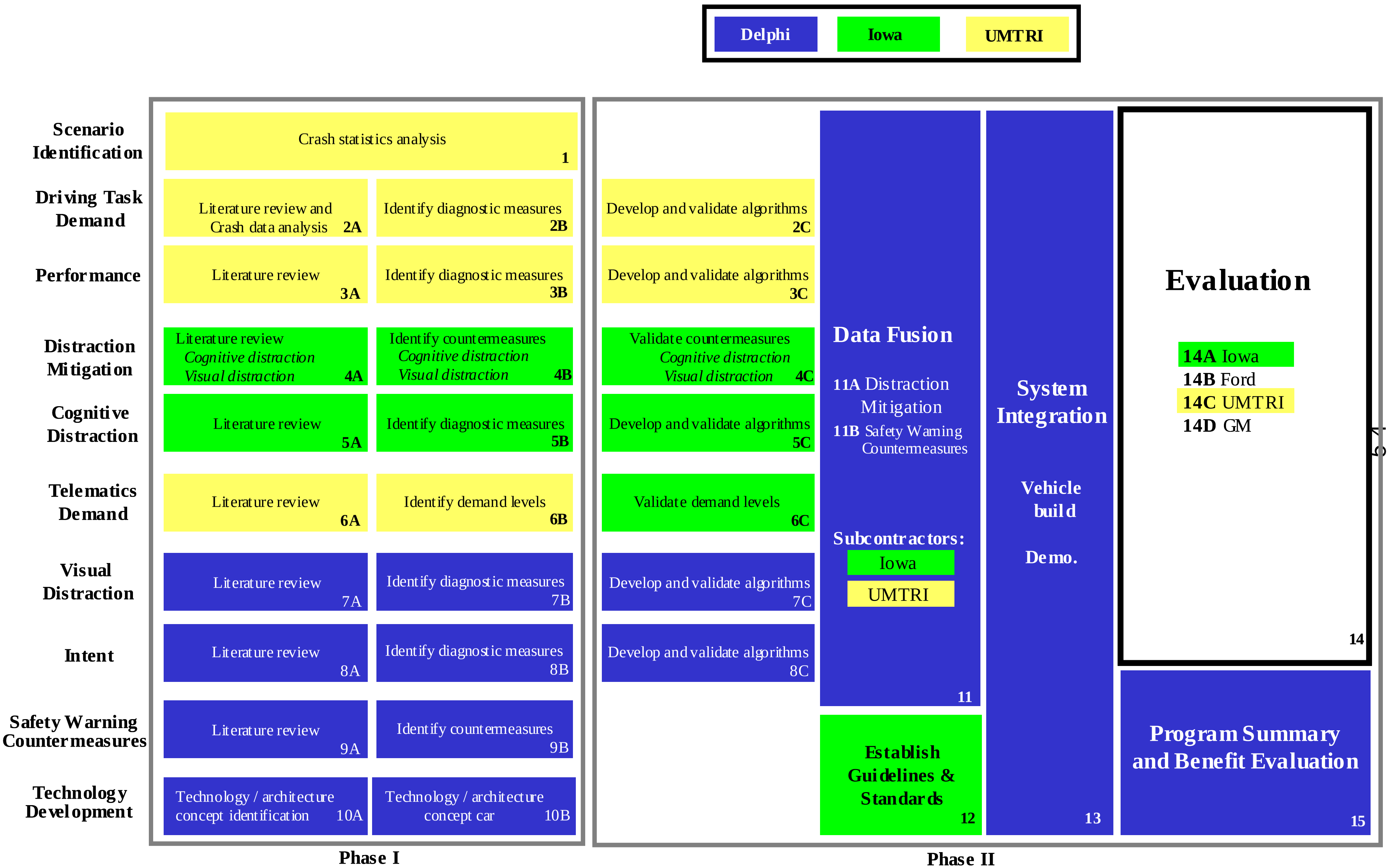

Figure i: SAVE-IT tasks

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.

[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.

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

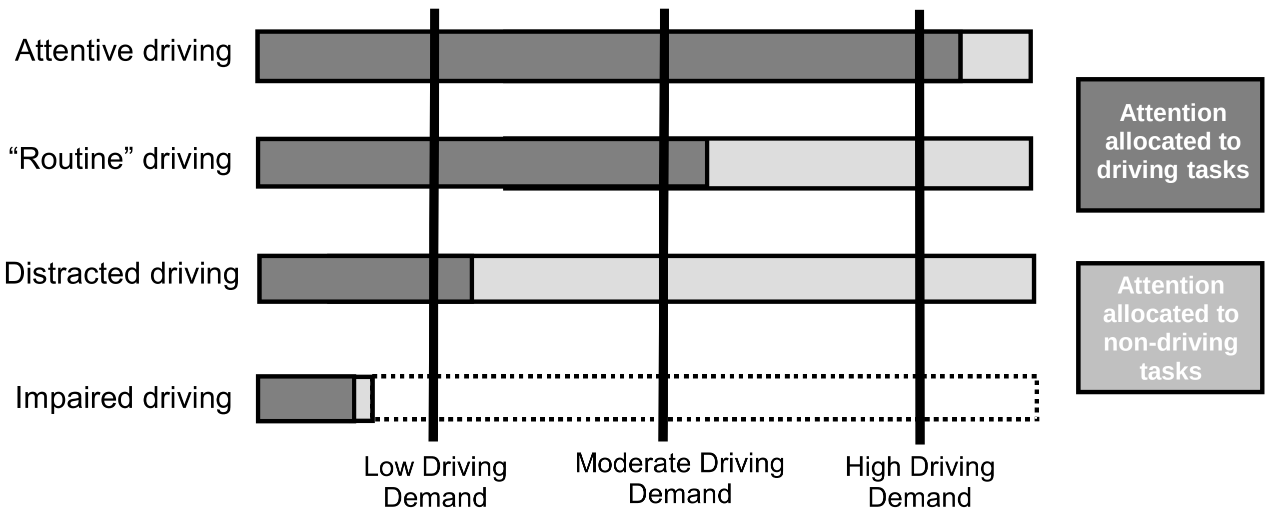

Figure ii. Attention allocation to driving and non-driving tasks

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

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

Communication and Commonalities Among Tasks and Sites

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

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

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

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

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

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

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

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

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

The Content and Structure of the Report

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

5.1 INTRODUCTION

Just as computers have transformed the office in the last 20 years, they will transform the car in the next decade. Recent advances in sensor, wireless, computing, and Global Position System (GPS) technology make sophisticated in-vehicle information systems (IVIS) feasible. These advances, combined with societal trends for increased productivity and the diffusion of work beyond the traditional office environment, will make these systems a reality. Computer, software, telecommunications, and automotive companies have begun to develop IVIS functions in anticipation of a $15 – $100 billion IVIS market (Ashley 2001; Lee, McGehee et al. 2002; Lee, McGehee et al. 2002) Unlike the desktop domain, in-vehicle information system (IVIS) functions require timesharing with the safety-critical task of driving. Failures of drivers to effectively timeshare and balance the demands of the roadway with those of in-vehicle tasks results in decrements in driving performance that can be labeled as distraction. Task 5 (Cognitive Distraction) fits into the SAVE-IT program by examining the nature of cognitive distraction so that estimates of distraction can be used to adapt the vehicle and reduce distraction and its effects on driving safety (Task 4: Distraction Mitigation).

Longer commute times, pressures for increased productivity, and increasingly powerful technology all stimulate IVIS development. In the United States, drivers have seen a steady increase in commute time, with a third of the 350 hours spent driving each year devoted to commuting (Hu and Young 1999). Decreasing average speeds on freeways, the associated increase in traffic congestion, and an emphasis on increased productivity from employers have contributed to the pressure to make time in the vehicle more productive. IVIS technology enables drivers to use driving time to do tasks otherwise done at the office, such as making telephone calls, managing email, and retrieving information. Computing anytime, anywhere, and for anyone seems to be the slogan of the next phase of the technological revolution. Market research firms estimate that the worldwide telematics market will grow dramatically in the next decade. By the year 2006, the world telematics market for personal vehicles is expected to be a $13 billion business, of which recurring annual revenues for services such as satellite-based digital area radio services (SDARS) broadcasters, XM Satellite Radio, and Sirius Satellite Radio will account for at least $4 billion (Viquez 2001). By 2005, approximately 85% of new vehicles sold will offer telematics as a factory or dealer-installed option (Morri 2001). A provocative estimate of the growth of IVIS devices compares them to personal computers. The number of personal computers per 1,000 people expanded from six to 200 from 1980 to 1990. A similar trend may occur in the next ten years, with IVIS-equipped vehicles growing from four per 1,000 to 195-200 by 2010 (Juliussen and Magney 2001).

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 (Sussman, Bishop et al. 1985; Wang, Knipling et al. 1996; Stutts, Reinfurt et al. 2001). 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, Mironer et al. 1993).

The cognitive demand of cellular phone conversations and their contribution to driver distraction is well documented. Cellular phone use can cause marked changes in the visual inspection patterns of drivers, such as reduced inspection of the mirrors, roadway, and speedometer (Recarte and Nunes 2000). Cellular phone use also causes an increase in the latency of reaction time to driving events (Alm and Nilsson 1994; Alm and Nilsson 1995), degrades perceptual judgments (Brown, Tickner et al. 1969) and undermines decision making (Cooper, Zheng et al. 2003). Hands-free cellular phones may help to alleviate the physical demands on the driver, thus reducing driver distraction and increasing driver performance. However, hands-free cellular phones may not reduce crash risk (Redelmeier and Tibshirani 1997) and can still impair braking response (Lamble, Kauranen et al. 1999). Not only do holding and dialing the phone undermine driver performance, but the cognitive demands of conversation also distract drivers' attention from the road. Many other types of in-vehicle technology may also demand drivers' attention and pure speech interaction with these devices can also result in levels of cognitive distraction that can impair driving performance (Lee, Caven et al. 2001).

Because distraction is a substantial contributor to crashes, particularly to rear end collisions and the distraction potential of cognitive demands are well documented, 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. To address this goal, this report reviews previous efforts to create adaptive systems. It also identifies a theoretical basis for predicting distraction using these variables, defines variables that might predict distraction (e.g., gaze variability, steering entropy, and infotainment device state), and examines potential algorithm alternatives that can be used to estimate distraction-related reaction time decrements in an unobtrusive, timely, and accurate manner. This review concludes with a description of two experiments that could help resolve issues regarding distraction measurement and prediction. Specifically this report includes the following sections:

5.2 OBJECTIVES AND OVERALL APPROACH

The objective of this task is to identify diagnostic measures of cognitive distraction and develop an algorithm that uses these measures to predict 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 will be 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). In addition to these variables, it is important to consider characteristics of the driving environment (e.g. type of road, weather conditions, traffic density); however, these roadway characteristics will be addressed in Task 2 (Driving Task Demand). The underlying assumption of this strategy is that each variable alone will be a moderate predictor of distraction-related reaction time decrements, but in combination they will be a strong predictor of distraction. Figure 5.1 shows that good estimates of cognitive distraction can also predict other driver performance decrements, such as speed and position control and event detection; however, the current project will focus on estimating the effect of distraction on reaction time.

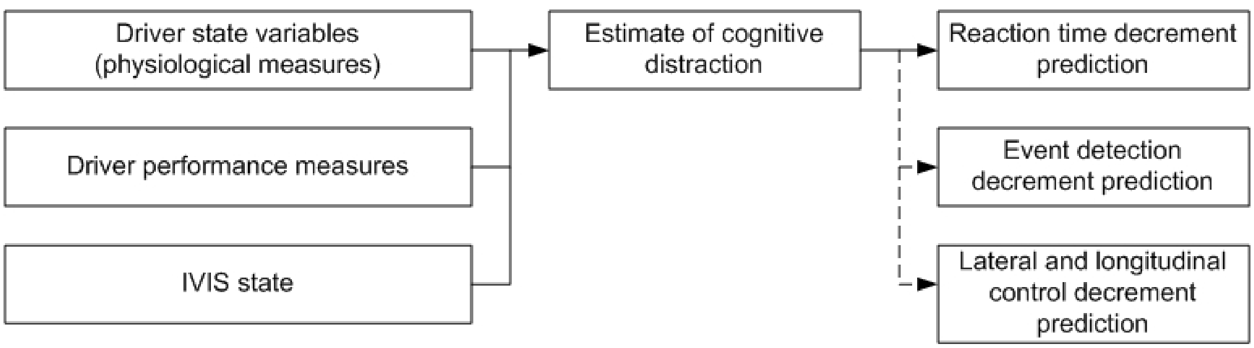

Figure 5.1. Convergent measures of cognitive distraction combine to predict reaction time decrement.

Once decrements of driver reaction time can be estimated, adaptive information displays and other distraction mitigation strategies can be implemented. For example, warning thresholds of collision warning systems could be adjusted to compensate for increased driver reaction time associated with periods of high levels of cognitive distraction. The particular mitigation strategies and the role of the distraction estimates in guiding these strategies fall outside the scope of this task; these are, however, addressed by Task 4 (Distraction Mitigation).

5.3 ADAPTIVE AUTOMATION AND DISTRACTION MITIGATION

This project is not the first to consider how technology might be used to measure and overcome problems of driver distraction, workload, and fatigue. Numerous research programs in the past fifteen years, both in the United States and abroad, have investigated the issues of driver workload and distraction and have explored ways to enhance driver safety through improved technology. A recent review compiled by TNO Human Factors, considered research regarding workload management systems that monitor driver, vehicle, and roadway state to assess driver workload and adjust vehicle systems accordingly (Hoedemaeker, de Ridder et al. 2002). The review identified several projects sponsored by the European Union (EU) and two non-EU projects with research focused in these areas. An initiative named Generic Intelligent Driver Support (GIDS) had the overall objective to assist drivers by controlling the flow of information from various systems to the driver. The integrated driver support system utilizes a central Analyst/Planner made of two modules, the Maneuvering and Control Support Model and the Workload Estimator, to control the timing and display modality of messages presented to the driver. Evaluation of this prototype found that, in general, driver workload was less when the support and information system was integrated than when it was not. GIDS studies also found that visual and cognitive workload were most influenced by traffic situation. A follow-up to the GIDS initiative, a project named Application of Real-time Intelligent Aid for Driving and Navigation Enhancement (ARIADNE), expanded the GIDS system and found that in addition to situation, driver experience and age contribute to visual and cognitive workload.

The project named Integration of Navigation and Anticollision for Rural Traffic Environment (IN-ARTE) sought “to improve traffic safety in rural environments” with an integrated driver support system designed to combine information from radar, sensors, and navigation maps in order to create an “extended view of the environment in front of the vehicle.” Experiments to investigate the effects of tactile versus speech messages found that speech messages caused momentary but rather large increases in workload while tactile messages did not. Experiments investigating driver acceptance of brake intervention and various warning threshold levels were also conducted. In general, drivers rated the brake intervention system positively, but they also tended to adopt longer headways, possibly to prevent the interventions. Drivers rejected all warnings of speed limit violation and ratings for upcoming curve warnings were most positive when the timing was such that the deceleration level was approximately 2 m/s^2. Ratings for warnings of a braking lead vehicle or obstacle ahead were also most positive when the deceleration criteria were 2 m/s^2 to 4 m/s^2.

A fourth EU-sponsored program identified by TNO, the Communication Multimedia UNit Inside CAR (COMUNICAR) project, set out to design and test a multimedia interface to control the timing and type of messages presented to the driver. The system includes an Information Manager and a Driver Workload Estimator, and both visual and haptic multimedia layouts were developed. Early testing results showed that both layouts were candidates for further development and a task-by-task analysis found that workload is influenced more by the type of task to be performed than by the type of interface.

DAISY, an adaptive, knowledge-based Driver Monitoring and Warning System (Onken 1994), part of the PROMETHEUS project, includes a learning module to create a behavior model of each driver and then uses this model to deliver warning messages adapted for that particular driver. Experiments in a fixed-based driving simulator and a test vehicle equipped with computer vision found a number of encouraging results, including the feasibility of monitoring and warning using computer vision data and, if enough learning time is allowed, and the feasibility of modeling the behavior of individual drivers. The haptic warning led to greater safety in situations where distraction was likely to occur. The results also showed that drivers demonstrated “risk compensation effects” by adapting to the warning system. Risk compensation is an important issue that should be considered when designing systems to increase driver safety.

The final project identified in the TNO review as relevant to research in the areas of driver workload and distraction and improved driver safety is the Co-DRIVE program, which uses a “Supremely Intelligent Co-driver Interface” to estimate the traffic risk, estimate workload, and set message priorities. The system uses an open platform so that each sub-system or service can present the driver with its own interface through the overall Co-Drive interface, which can disable certain services if the risk for distraction is too high. The TNO review does not discuss any results of the Co-DRIVE program.

Overall, the TNO review concluded that many of the European projects reject the practice of estimating a driver’s momentary workload, due to the complexity of this method, opting instead for one or a combination of two other possible methods. The first is the possibility of estimating driver workload from driver behavior. The second is a look up table that relates factors affecting workload, such as characteristics of the driver and the driving environment, to estimate levels of workload. Our approach illustrated in Figure 5.1 encompasses all three methods, aiming to monitor workload through the convergence of real-time driver physiology and performance measures as well as the workload demands associated with IVIS interactions.

The TNO review also highlights system intervention (i.e., when the system takes over part of the driving task, such as steering or braking) as a particularly important challenge. These types of mitigation strategies have not been popular with car manufacturers due to liability in the event of failure or malfunction. Finally, the review points out that little attention has been given to studying the acceptance of such adaptive systems. Driver acceptance should be considered both during the detection and the mitigation of driver distraction.

Several electronics and automotive companies have also initiated separate approaches to workload management systems. As an example, Motorola has created the Driver Advocate, which monitors a wide range of information from the driving environment as well as driver behavior and state variables to identify appropriate advice and alerts. Like the SAVE-IT program, the ultimate aim of this system is to predict driver distraction and focus the driver’s attention on the task that is the most important for safety.

Beyond the automotive domain, substantial research has addressed the concept of adaptive automation (Rouse 1976; Chu and Rouse 1979). Adaptive automation adjusts the degree of automation to compensate for the limits of the human controller. For example, automation aiding a pilot might take over some flight tasks if the pilot becomes overburdened and unable to complete them. As in this project, the objective of many of these systems has been to use physiological variables, such as heart rate, skin conductance, and EEG signals, to estimate workload (Prinzel, Freeman et al. 2000; Scallen and Hancock 2001). Although the focus of much of this research has been on estimating operator workload so that automation can be engaged to avoid overload situations, adaptive automation has also been considered for situations in which the problem is underload rather than overload. In these situations, monitoring for underload situations and then returning control to the operator can enhance performance (Byrne and Parasuraman 1996). These issues are explored in more detail in the review of distraction mitigation strategies as part of Task 4.

In conclusion, this previous research identifies several issues to consider when devising a method for detecting driver distraction. These include:

- Driver characteristics such as age and level of experience, both with the driving task and with the various IVISs, seem to be very important.
- Driver adaptation to the IVISs such that the safety benefits are eroded as drivers take advantage of the increased ability to do non-driving tasks as they drive.
- The use of driver-specific models for detecting and mitigating distraction should be considered.
- Driver variables should be monitored for signs of both overload and underload, particularly as vehicle automation (e.g., adaptive cruise control) reduces drivers' vehicle control interactions.
- The demands of the IVIS, including the types of tasks drivers perform with them as well as modality the tasks are displayed in, play an important role in momentary driver workload.
- The extent to which the different IVIS devices are integrated has important implications for the cognitive demand they impose on the driver.
- Finally, driver acceptance of a device to detect and mitigate distraction is critical so that the system will not be subject to misuse or abuse.

Given the scope of these considerations, our approach of measuring distraction by considering a wide variety of driver physiological and performance measures along with the IVIS state seems appropriate. The following section describes types of distraction and explores the relationship between workload and distraction.

5.4 DISTRACTION AND WORKLOAD

Distraction occurs when a driver "is delayed in the recognition of information needed to safely accomplish the driving task because some event, activity, object, or person within or outside the vehicle compels or induces the driver's shifting attention away from the driving task" (Stutts, Reinfurt et al. 2001). Several other researchers have gone beyond this definition of distraction to specify the particular ways in-vehicle devices distract drivers. Visual and manual demands are particularly important contributors to distraction, which can be separated into five categories according to the degree of visual and manual involvement: manual only, visual only, visual primarily, manual primarily, and visual-manual (Wierwille 1993). Manual only tasks require no visual confirmation after they are learned. Turn signals and other simple controls are good examples of manual tasks that make no visual demands. Other interactions make visual and manual demands. One example of this is tuning the radio, which requires visual glances to the display and manual adjustment of the tuner. The visual component of these tasks degrade both vehicle control and the detection of objects and events in the driving environment, and the manual component can interfere with steering and lateral control (Tijerina 2000).

The simple combinations of visual and manual contributors to distraction have been expanded upon by more recent descriptions of distraction. Ranney, Mazzae, Garrott, & Goodman (2000) identified four components of driver distraction: (1) visual (e.g., eyes-off the roadway), (2) auditory (e.g., conversing with other passengers), (3) biomechanical (e.g., manually adjusting the radio), and (4) cognitive (e.g., being lost in thought). Manual distraction or biomechanical interference is caused by the driver's "body shifts out of the normal position" while performing tasks such as reaching for controls or a cell phone, eating, or smoking (Tijerina 2000). The interference associated with cognitive distraction occurs even in the absence of structural interference that occurs when drivers take their eyes off the road or remove their hands from the steering wheel. Cognitive distraction will be the focus of this review, but because purely cognitive distraction is unlikely, it is important to consider the potential interactions between the different types of distraction.

Cognitive distraction occurs when cognitive activity (e.g., working memory, long-term memory retrieval, response selection, or executive control) associated with a non-driving task interferes with perception, processing, and/or response to the roadway environment. This definition of cognitive distraction is consistent with the more general types of distraction and will guide and delimit the analysis of how cognitive distraction can be measured and reduced. 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.

Distraction and driver workload are two terms that are interrelated and many researchers equate cognitive distraction with mental workload or information overload. Several recent research programs have addressed distraction from the workload perspective for in-vehicle system design. Three of these programs have specifically tried to address the potential of IVISs to distract drivers through overload: GEM, IVIS DEMAnD, and HASTE. A fourth program within the Crash Avoidance Metrics Partnership (CAMP) also aims to develop workload metrics to be applied to IVIS design.

The EU-sponsored Generic Evaluation Methodology for integrated driver support applications (GEM) project set out to create a method for assessing how new driver support systems might affect driver performance and what effect different combinations of systems could have on performance. GEM identified numerous methods to evaluate a system based on the characteristics of its interface and considered at what developmental stages different evaluation methods could be used, the costs of applying different methods, as well as how long system interaction lasted and the level of "loading" the system imposes on the driver. Although the compiled information about the available evaluation methods is useful, the TNO review concludes that the GEM Project did not meet its objective of creating a generic methodology to evaluate of integrated support systems (Hoedemaeker, de Ridder et al. 2002).

The In-Vehicle Information System Design Evaluation and Model of Attentional Demand (IVIS DEMAnD) project had a goal similar to GEM's. It set out to help IVIS designers estimate how much demand their prototype systems would place on drivers. The IVIS DEMAnD software allows the user to identify one or more of five different resources that IVISs can require: visual demand, auditory demand, supplemental information processing demand, manual demand, and speech demand. The application also contains a library of tasks, and a wizard can help the user define a new task if it is not currently in the library. Finally, the user identifies parameters of the design that can be modified, and the software presents conceptual measures of relative driving task performance and a demand measures summary (Monk, Moyer et al. 2000).

Another European research program currently in progress, the Human Machine Interface And the Safety of Traffic in Europe (HASTE) Program, has the objective "to develop methodologies and guidelines for the assessment of In-Vehicle Information Systems (IVIS)" (HASTE 2003). The program will consider the risk associated with using an IVIS in different traffic conditions, "identify the best indicators of risk," and "recommend a pre-deployment test regime … to predict performance." The aim of this program is quite similar to the ongoing collaboration between Ford Motor Company, General Motors Corporation, and others to develop driver workload metrics as part of CAMP. The objective is to "develop practical, repeatable driver workload metrics for both visual and cognitive demand that can realistically assess which types of driver interface tasks are appropriate to perform while a vehicle is in motion. It will then identify interface design approaches which emerging collision avoidance and comfort and convenience oriented information systems might employ in order to provide acceptable workload performance ratings" (CAMP 2000).

As defined by Hart and Wickens (Hart and Wickens 1990), "workload is a general term used to describe the cost of accomplishing task requirements for the human element of man-machine systems. This 'cost' may be reflected in the depletion of attentional, cognitive, or response resources, inability to accomplish additional activities, emotional stress, fatigue, or performance decrements." Many argue that mental workload is synonymous with effort (Moray 1979; Moray 1988). As Figure 5.2 shows, workload and performance are dependent upon the task demands presented by a specific system and the strategy chosen by each operator for that specific situation (Hart and Wickens 1990). For example, drivers may adopt different control strategies or accept lower performance (e.g., relax the safety margin and allow the car to get closer to the lane boundary) to keep effort constant when they engage in IVIS tasks. Alternatively, they may reduce their effort, shift attention to the IVIS task, and neglect the roadway demands.

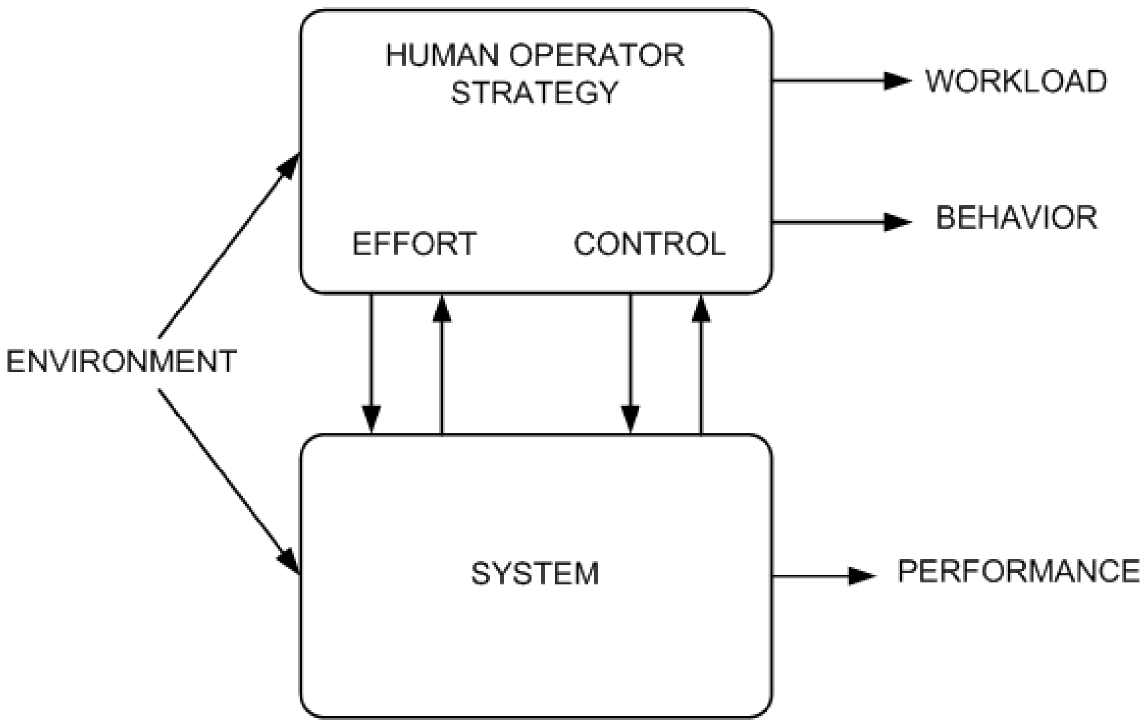

Figure 5.2. Conceptual framework relating operator performance and workload (Hart and Wickens, 1990).

Figure 5.3 shows how effort, driving safety (maintaining safety boundaries), and productivity (degree of engagement with IVIS tasks) might relate. For a given level of effort, drivers could achieve various degrees of safety or IVIS productivity. Likewise, increasing effort could lead to higher levels of IVIS productivity and/or safety depending on the feedback available to the driver and the driver's internal performance criteria and values. This figure demonstrates that treating drivers as passive recipients of the IVIS demands will not predict distraction-related decrements in driving safety.

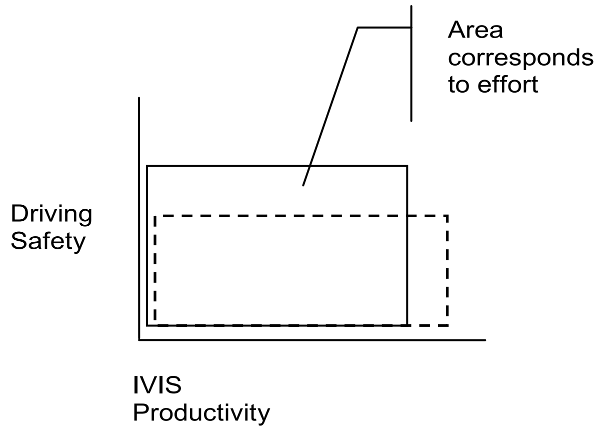

Figure 5.3. An example of how driving safety might decline when workload (effort) declines if a driver (shown by the dashed line) decides to allocate effort towards IVIS tasks rather than driving, compared to another driver (shown by the solid line) who suffers a higher workload, but focuses on driving and is safer as a result.

Although the interference of multiple in-vehicle and driving tasks can lead to distraction and the neglect of driving tasks, high levels of workload or information overload do not explain all distraction-related decrements in driving performance. In fact, distraction and an associated decrease in performance can occur with low workload levels. The relationship between performance (dashed line) and operator effort (solid line) for a specific set of task demands is seen in Figure 5.4. In region D, the low task demands undermine performance as drivers work to overcome boredom and maintain vigilance. As the level of demand increases, region A1 is entered and operator workload decreases as the additional tasks demands reduce the effort to stay engaged with the driving task. Region A2 is the region in which performance and effort remain steady as demand increases. Throughout region A3, increased operator effort is required to maintain a high performance level with increasing task demand. Finally, the demands become so high that the operator cannot maintain performance despite increased effort and so regions B and C are encountered. Regions B and C are of concern when considering distraction caused by the overloading of cognitive resources, while region D represents the challenge drivers face when trying to remain vigilant to rare, but important events, such as a braking lead vehicle on an interstate highway.

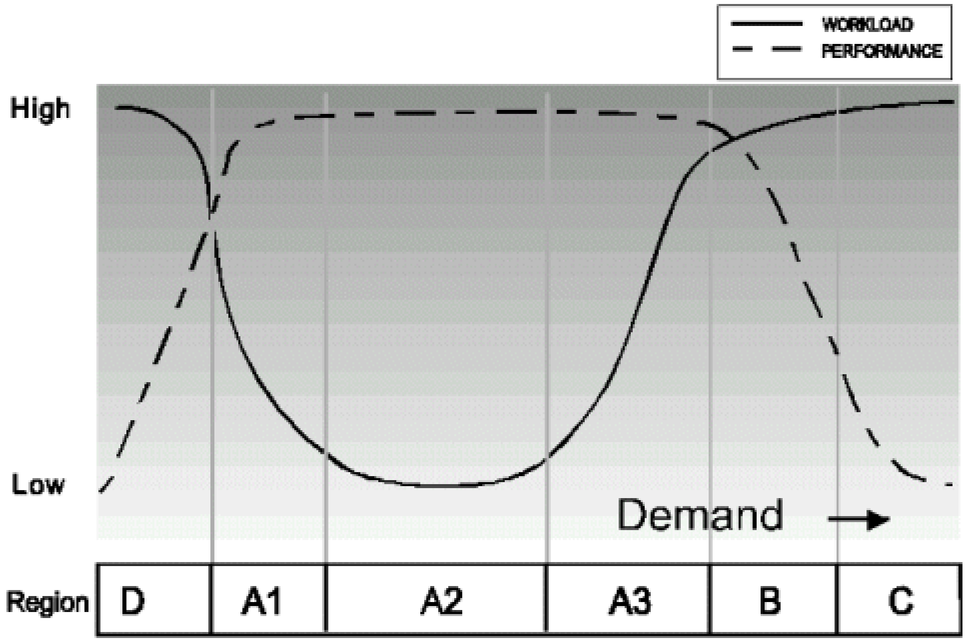

Figure 5.4. Operator performance and effort as a function of task demand (de Waard, 1996).

Although cognitive distraction can be the result of either overload or underload, it is clear that these conditions occur as the result of very different situations and manifest themselves differently. Thus, it seems logical that the detection of cognitive distraction as the result of overload might require different information or methods than the detection of cognitive distraction resulting from underload. It also seems useful to make a distinction about what cognitive processes are at the root of the distraction in order to determine if mitigation is required and if so, how the mitigation should take place. For example, if a driver is experiencing capacity overload, distraction might be revealed by physiological measures associated with stress or high levels of arousal. The mitigation strategy for a driver in this situation may be different than the mitigation strategy for a driver who is distracted through underload.

The problems of excessively high and low task demand identify important considerations for the measurement of distraction and its mitigation. The mechanisms associated with how drivers accommodate these extremes may help reconcile potential dissociations between variables related to distraction and prediction of reaction time decrements. In particular, multiple resource theory (MRT) offers a powerful framework for understanding likely situations where cognitive tasks will exceed drivers' capabilities and interfere with safety-critical driving tasks (Wickens 1984; Wickens 2002). Issues of overload that are the focus of MRT are not the only contributors to distraction; underload is also important, particularly as automotive automation becomes increasing capable. The concept of malleable attentional resource theory describes the cognitive mechanisms associated with underload and workload transitions from underload to overload that also contribute to problems of distraction (Young and Stanton 2002a; 2002b). Current research regarding distraction tends to focus on excessive levels of workload as a basis for distraction. Taking into account the concept of workload more generally identifies the following considerations that must be examined to better understand distraction:

- Workload depends on multiple aspects of the task(s) (e.g., visual, manual, and cognitive components).
- Both the environment and the system contribute to the demands that confront the driver.
- Control strategies and performance criteria greatly influence the level of effort expended and workload experienced by the driver.
- Withdrawal of effort from driving tasks and focus on IVIS tasks can degrade safety without any indication of information overload.
- Conditions of underload can lead to distraction-related performance decrements, particularly transitions from underload to overload situations.

The following section provides a theoretical basis for measuring, predicting, and mitigating cognitive distraction.

5.5 THEORETICAL BASIS FOR INVESTIGATING COGNITIVE DISTRACTION

When drivers perform other tasks while driving, such as interacting with passengers, using an IVIS, talking on a cell phone, or eating, they are engaged in multi-tasking. If perfect timesharing takes place, all the tasks will be performed at the same level as if they were each performed alone. Many times, however, performance on one or more of the tasks is compromised. If the driving task is one of these, there can be serious safety consequences. A large body of research has addressed dual-task performance, the simplest instance of multi-task performance. Several theories of attention and workload have been proposed to explain the performance decrement that sometimes occurs during dual-tasking, including single channel and multiple resource theories, malleable attentional resource theory, and strategic task management. All provide insight into the mechanisms underlying the problems of cognitive distraction.

5.5.1 Multiple resource description of dual-task performance

A long history of dual-task performance research provides a foundation for considering driver distraction. Telford (1931) discovered that as the interval between two presented stimuli decreased, the response time for the second one increased. Telford called this slowing the psychological refractory period (PRP). Craik (1948) presented participants with a continuous tracking task which they completed using discrete movements. Craik accounted for this behavior by proposing the occurrence of a central "computing" process that is either delayed by new incoming information or somehow blocks it out. He concluded, "there is a minimum interval within which successive stimuli cannot be responded to." Five years later, Welford (1952) stated that central mechanisms can only deal with information from one stimulus at a time. These and other early theories were global single-channel hypotheses that did not identify what particular processes between stimulus presentation and response execution were included in the central processes that led to the response delay. Subsequent research has provided evidence for and against placing the bottleneck at different stages, including perception, response selection, and movement production (for a review, see Meyer and Kieras 1997; Pashler 1998). Since the exact location of the bottleneck could not be located, Kahneman (1973) proposed that a general-purpose processing capacity, namely attention, could be allocated to different processes. However, this unitary resource theory predicted that interference would occur even if two activities did not share perceptual or response mechanisms, a prediction that has been refuted through the near perfect timesharing of multiple tasks. To account for these data the theory of multiple resources was developed (Wickens 1984).

Wickens developed multiple resource theory (MRT) by reviewing the literature pertaining to dual-task performance and identifying "the particular structural dimensions of human information processing that meet the joint criteria of accounting for changes in time-sharing efficiency, and being associated with neurophysiological mechanisms which might define resources" (Wickens 2002). With this approach, multiple and independent attentional limited capacity resources govern dual-task performance. MRT states that there are resources located on several different dimensions that can be allocated to different tasks. These resources are not singular in nature, but the capacity of these resources is fixed. A performance decrement in the dual-task situation is seen only if the tasks compete for the same resources. Multiple resource models can be used to predict whether interference is likely or unlikely to occur in dual-task situations. One such multiple resource model, proposed by Wickens (2002) and represented in Figure 5.5, has four dichotic dimensions.

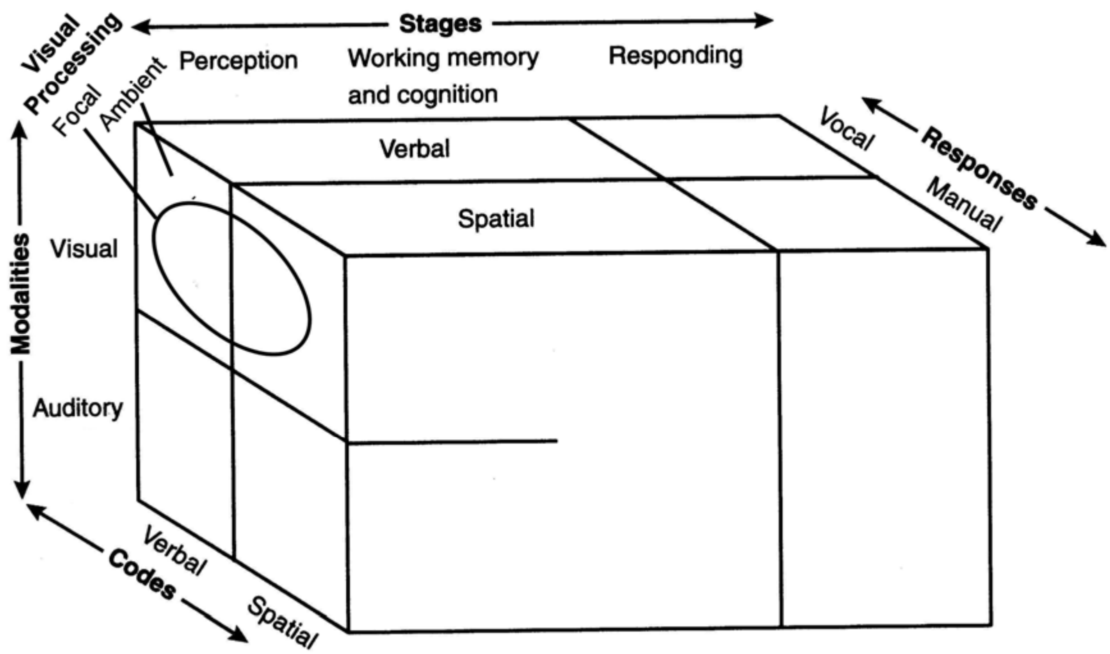

Figure 5.5. Three-dimensional representation of the structure of multiple resources. The fourth dimension (visual processing) is nested within visual resources (Wickens, 2003).

The first dimension is the perceptual modality required for each task. The two components of the dichotomy are the auditory and visual channels. Two tasks requiring visual perception, such as driving and reading a map, heavily compete for visual resources. Trying to discriminate between two streams of auditory messages is quite a difficult task, as the streams will tend to mask one another. However, if information for one task is presented visually while information for the second task is presented through an auditory channel, then improved dual-task performance with less interference is likely to be seen. Nested within the visual perceptual modality are focal and ambient vision resources of the visual processing dimension. Focal vision is necessary to recognize fine details and patterns while ambient vision “is used for sensing orientation and ego motion.” These resources aid a driver in maintaining lane position while fixating on a roadside sign or checking mirrors.

The third dimension is the modality in which information is coded, with the two resources being verbal or spatial coding. Since driving is primarily a spatial task, MRT would suggest the use of verbal coding for any secondary task. The spatial and verbal coding resources also tend to correspond to manual and verbal response, respectively.

An example of the kind of interference that can occur when two tasks share the same coding can be seen when one tries to read and listen at the same time. While the two tasks use separate perceptual resources, both are coded verbally.

The fourth dimension is the level of perceptual processing required to complete each task. The processes of perception and cognition use different resources than the selection and execution of responses. Thus a stimulus can be perceived and identified while a response to another stimulus is prepared and executed. However, the resource for response selection can only be allocated to one task at a time. This observation is complementary to Pashler's (1998) finding that a bottleneck occurs at the stage of response selection, which he calls "central processing." Pasher found that two independent responses cannot be selected at the same time, while perception of another stimuli or execution of another response can occur concurrently with response selection. This dimension is particularly important for predicting driver distraction because it suggests that activities that require response selection will interfere with each other to a great degree, even if they are perceived and responded to using different resources. Specifically, a task such as listening to an audio book that does not require response selection should not interfere with driving as much as participating in a conversation, as both the conversation and driving tasks require responses from the driver. Findings by Strayer and Johnston (2001) confirm this prediction, as participants performed significantly worse on the 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 have an impact on two tasks even when they do not share perceptual or coding resources.

The assumption of multiple tasks competing for limited resources contained within this theory is a powerful heuristic for describing dual-task decrements. More generally, this perspective of resources of limited capacity provides the theoretical basis of most descriptions of workload. This approach can be used to predict driver distraction caused by conflict between specific driving maneuvers and certain in-vehicle tasks. For example, while focal vision is required to read a visually presented in-vehicle message, ambient vision can be used to maintain lane position. However, the performance of event detection, part of the driving task that requires focal vision, would be expected to suffer.

Quantitative models of driver performance have used MRT to predict the effect of different types of distraction. For example, Boer (2001) described twelve non-driving tasks according to the types of resources they demanded. Driving performance, as defined by steering behavior and reaction time to unpredictable events, was measured as drivers completed each of these twelve tasks. Consistent with the MRT, he found that tasks that demand spatial resources tend to affect steering performance most and tasks that demand verbal resources tend to have the greatest effect on event detection. Interestingly, most of the control interference depended on the response/execution stage of the tasks, which is consistent with Pashler's (1998) assertion that performance is limited by a response bottleneck.

One of the primary assumptions of MRT is that resources have a fixed capacity that remains constant over time. Recently this assumption has been questioned, as decreased performance has occurred in situations with reduced task demands. These results contradict the MRT prediction of increased performance with decreased demand. However, if resource capacity does indeed fluctuate over time, extended periods of decreased demands may lower resource capacity. A recent theory, malleable attentional resource theory (Young and Stanton 2002b), suggests just that, and the factors that reduce capacity may be important contributors to the problem of driver distraction.

5.5.2 Malleable attentional resource theory

Malleable attentional resource theory describes the factors that can diminish resource capacity and predicts performance decrements that the mental overload approach to distraction does not. While MRT is useful in predicting cases where mental workload required by task demands may exceed the available attentional resources to produce overload performance decrements, it fails to account for situations where poor performance is seen despite low task demands. Malleable attentional resource theory addresses the role of low mental workload on performance (Young and Stanton 2002b). The theory proposes that the level of available attentional resources is flexible instead of fixed, and in situations of low workload attentional resources will shrink to "accommodate any demand reduction." This concept is shown in Figure 5.6. If the operator is working on a high demand task when a failure event occurs, the level of attentional resources available is sufficient to handle the event. However, if the capacity of attentional resources has been reduced due to a low demand task, the operator will not be able to handle the failure event.

In order to test the malleable attentional resource theory, Young and Stanton (2002b) performed an experiment which tested performance on a visual-spatial secondary task while varying driver workload on a simulated driving task through various levels of automation: manual, adaptive cruise control (ACC) which controlled headway, automated lateral control (AS), and ACC+AS (fully automated). Participants were told that driving was the primary task and that the secondary task should be performed only when the driving task allowed. In order to determine whether or not the drivers' attentional capacity changed with workload, a measure called the attention ratio (AR) was derived from the secondary task data with the following formula:

$$AR = \frac{number\ of\ correct\ \mathrm{sec}ondary\ task\ trials}{time\ to\ perform\ \mathrm{sec}ondary\ task\ in\ \mathrm{sec}onds}$$

The AR values for the manual and the ACC conditions were not significantly different, but a significant decrease was found between the ACC and AS conditions, and between the AS and the ACC+AS conditions, suggesting that "the allocation of attention to the secondary task becomes less efficient" as mental workload decreases. Since the "participants' responses on the secondary task did not vary consistently with the amount of attention they directed to the task," the authors concluded that the size of the resource pool can change.

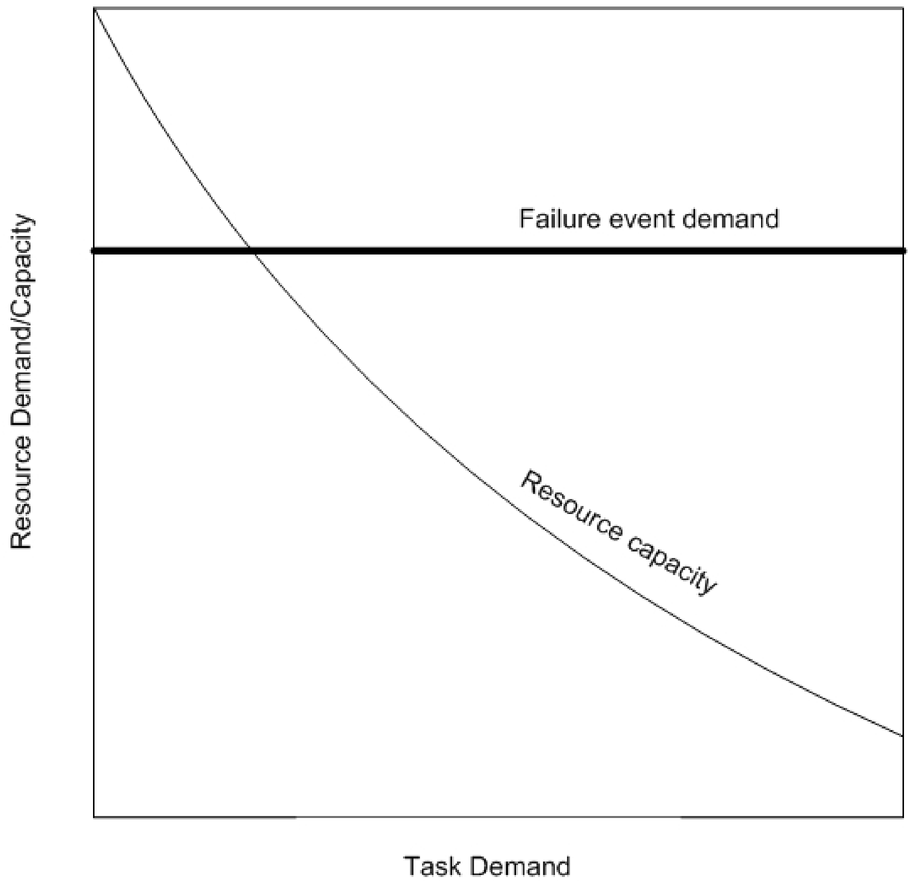

Figure 5.6. Pictorial representation of performance differences under a malleable attentional resources hypothesis (Young and Stanton, 2002a).

While this theory shows great promise in explaining the effects of driver distraction in the form of attentional withdrawal, further research needs to be conducted for a number of reasons. First, the reduced mental workload was not shown to have an effect on driving performance, most likely since only normal driving tasks and not emergency situations were investigated. Second, the authors acknowledge that the results obtained could have been the product of arousal alone and more research is needed to discover the role of arousal in determining resource capacity. Third, it is unclear whether the capacity of all resources are affected equally by lowered demand or whether certain resources are more susceptible. Finally, the mechanisms through which or the speed at which the attentional capacity modulates are not described or investigated.

Despite the many unknowns the theory has yet to answer, the main ideas behind malleable attentional resource theory pose important considerations for an algorithm to predict distraction. If the capacity of attentional resources can indeed change in a relatively short-term time period, the history of the driver state may play an important role in the prediction of driver distraction. For example, performance in a low demand situation followed by a high demand situation would be predicted to be worse than when a high demand situation is followed by a period of low demand. Thus, accurate predictions of distraction might need to consider how attentional resources may shrink during long low-demand periods, making the degree of distraction greater when driving demand increases abruptly. Such time-dependent effects cannot be accounted for by MRT. Issues like this are also important to consider when implementing mitigation strategies.

As an example findings that support malleable resources, Desmond, Hancock, and Monette (1998) exposed participants different levels of engagement in a driving simulator and then monitored their recovery to disruptions. In one condition drivers had complete control of the driving task while in the other condition the driving task was "controlled by an automated driving system." During each drive participants experienced disruptions, drifts from the roadway caused by wind gusts in the manual control condition and a failure of the automation system in the automated condition. Disruption recovery was better for the manual control condition than for the automated condition. These results correspond to the conceptualization of the malleable resource theory shown in Figure 5.6.

Although multiple and malleable resource theories provide a useful basis for understanding how driving and in-vehicle tasks interact to create distraction-related decrements in driving performance, they both focus on how attentional resources are shared in a dual-task scenario. These theories make several important assumptions that may be violated in many real-world driving situations and fail to address several key factors affecting multi-task performance. For example, most research supporting resource-based descriptions of human performance involve dual-task situations; however, driving and interacting with one or more IVIS creates a much more complex situation. Driving alone involves multiple tasks including: navigation, visual search for landmarks, hazard detection, speed selection, speed control, lane selection, and lane keeping. In-vehicle tasks can be similarly complex and diverse. The distraction-related decrements in driving may not be predicted by performance decrements of two simple tasks. Some important features of complex, multi-task environments that resource-based theories do not consider include:

- Task prioritization and the decision to engage in non-driving tasks
- Task preemption and attentional withdrawal
- Task scheduling and task switching rather than parallel processing performance
- Task complexity and its influence on task switching
- The effect of in-vehicle task demands on multilevel goal management

These important considerations are not addressed by resource based theories of multi-task performance but are considered under the general topic of strategic task management.

5.5.3 Strategic task management

The concept of strategic task management has been used by several researchers to describe decrements in multi-task performance in complex domains, such as aviation (Wickens 1984; Funk 1991; Funk and Kim 1995; Chou, Madhavan et al. 1996) and manufacturing (Moray, Dessouky et al. 1991). In the driving domain, a model of driver workload management was adopted for the Heavy Vehicle Driver Workload Assessment project instead of a traditional limited capacity resource model of mental workload (Wierwille, Tijerina et al. 1996). "Sandra Hart (1989) has been one of the most vocal proponents for such a shift in the workload domain. Her arguments are based on the premise that people 'actively manage their time, energy, and available resources to accomplish tasks on time and with adequate performance and, at the same time, to maintain a comfortable level of workload. To do so, they dynamically modulate their priorities, strategies, focus of attention and effort…'" (Adams, Tenney et al. 1991). Hart and others identified several reasons why the traditional laboratory approaches to investigating workload are artificial and may not address some aspects of the complex multi-task activity of driving, including (Hart 1989; Adams, Tenney et al. 1991; Wierwille, Tijerina et al. 1996):

- Pushing people to work to their limits denies the opportunity to adopt realistic coping strategies.
- Using trials measured in minutes rather than more realistic intervals of hours may misrepresent the level of effort people are willing to expend
- Forcing people to respond in particular ways (e.g. immediately and consistently) may not reflect the flexibility that exists in many driving situations
- Homogenous demands do not reflect the sequential, overlapping demands of various magnitudes with various costs and benefits that confront drivers.

Although dual task research and MRT do not address the full range of factors affecting the driver's ability to share driving and non-driving tasks, they provide a useful complement to the workload management approach. The driver workload management approach focuses on prioritization, scheduling, and effort allocation in balancing the demands of driving and in-vehicle tasks. This approach considers the factors that govern how drivers to divide their effort between the roadway and in-vehicle tasks and how the ability to switch between these tasks depends on the duration of the tasks, their complexity, how easily they can be interleaved, and how easily a task can be delayed and later resumed. Complementary research considering how drivers share their visual resources between the driving scene and an in-vehicle task has been completed. A simple task management model concerning the practice of visual sampling was posited by Wierwille (1993) and is shown in Figure 5.7.

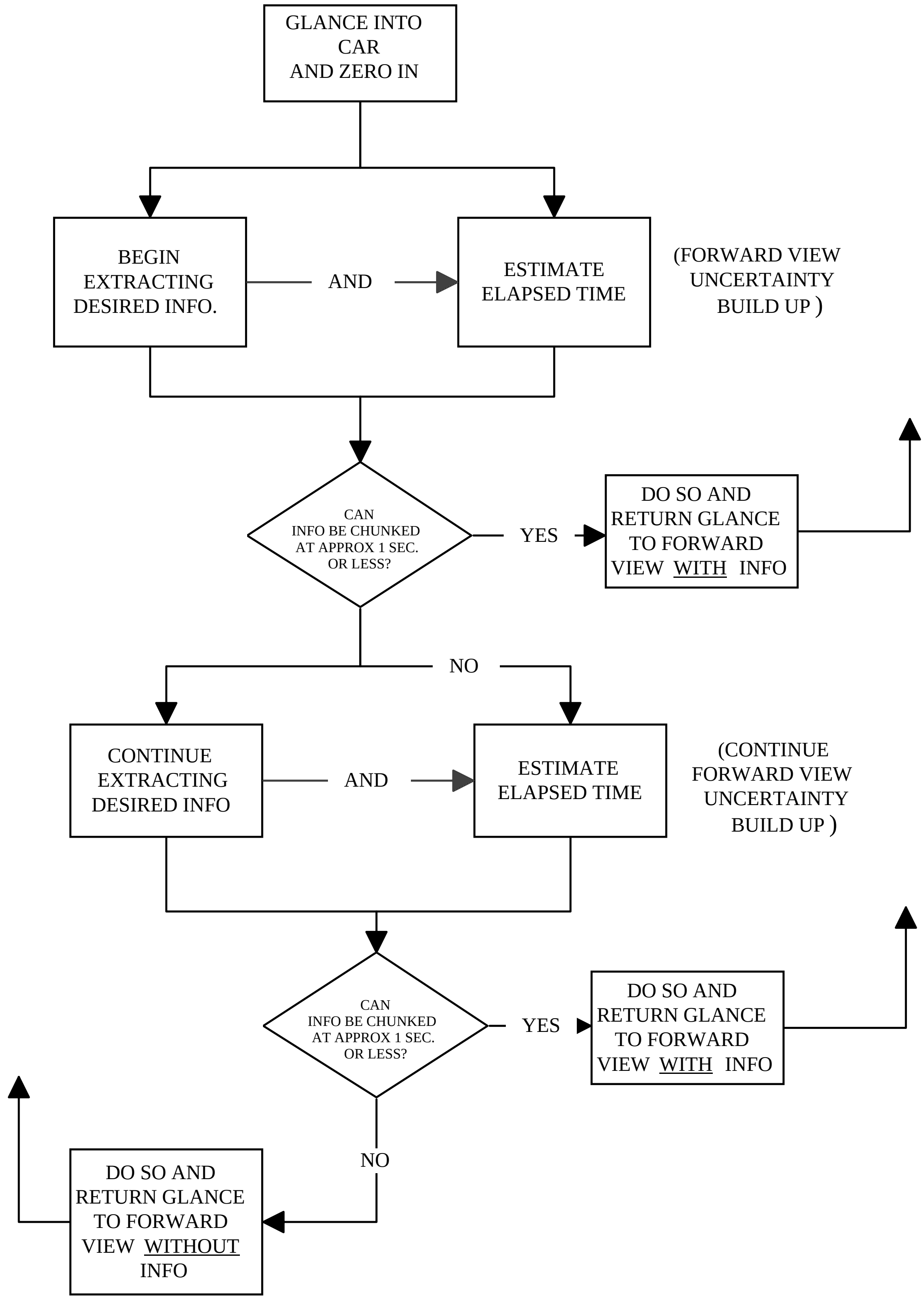

Figure 5.7. Model of visual sampling for in-vehicle tasks that shows the importance of strategic management of driving and in-vehicle tasks (Wierwille 1993).

This normative, deterministic model starts when the driver begins performing an in-vehicle task by glancing to an appropriate location. Information extraction begins as time elapses. If drivers can chunk information in one second or less, they will return their glance to the forward scene. However, if chunking takes longer, drivers will continue to glance at the location for a longer period of time. If this occurs, uncertainty builds up and drivers feel pressured to return to the forward scene. If the glance to the in-vehicle location continues up to approximately 1.5 seconds and the information cannot be obtained (or chunked), drivers will return their glances to the forward scene anyway and try again later. Additional samples are handled in the same way, until all required visual information is obtained. This simple model illustrates how the in-vehicle task characteristics interact with the driving demands and the driver's ability to appropriately allocate attention to affect driving performance decrements. Similar considerations need to be contemplated in the task management associated with cognitive demands.

Strategic task management involves monitoring the environment and determining the significance this new information has for the driver's goals, deciding whether to interrupt the current task and engage in another task, scheduling tasks in a queue according to priority, and evaluating and reorganizing the queue if necessary. Memory and experience are also important, as a new experience causes the driver to determine its significance while a response to a familiar event is less effortful (Adams, Tenney et al. 1991).

The interpretation of information from the environment is a process that requires time and effort. If too much time and effort are required, the task the driver is currently engaged in may be disrupted. On the other hand, information might be interpreted incorrectly if too little time and effort is put forth, causing the driver to misclassify the information and its relevance in relation to his or her goals (Adams, Tenney et al. 1991).

After environmental information is interpreted, the driver must use this information to decide whether or not to switch tasks. People tend to avoid interrupting a current task, even if there are benefits to doing so (Wood 1982; cited in Adams, Tenney et al. 1991). After a person decides to interrupt a task, their memory for the interrupted task persists and the person is predisposed to return to the task, an effect described by Ziegarnik. People remember the details of the task no less even if they know they will not resume the task (Zeigarnik 1965). The implications of the Zeigarnik effect on driver workload is that once drivers begin a task there is a strong tendency to finish it if interrupted. The tendency to complete an interrupted task grows with the relevance of the task to the driver's current goals and interrupted tasks may continue to make demands on working memory (Wierwille, Tijerina et al. 1996).

The actual mechanisms of task switching have been the focus of much research (e.g., Jersild 1927; Allport, Styles et al. 1994; Rogers and Monsell 1995). Task switching experimental paradigms generally use one stimulus to evoke two different responses. For example, a red square can signal one response based on its color and another response based on its shape. Which response is appropriate depends on whether the trial is a color trial or a shape trial. When the current trial differs from the previous trial, a decrement in response time and accuracy can be seen. This decrement is commonly called the “switching cost.” The research also shows that the switching cost can be reduced, but not eliminated, if one is able to prepare before the stimulus is presented. Two main theories have emerged to explain switching costs. The first argues that the cost of task switching can be described in terms of the tasks’ inertial properties. The second argues that switching costs depend on the processes associated with retrieving condition-action rules.

The Task Set Inertia (TSI) theory proposes that the switch cost occurs because the task set used on the previous trial before the switch must be inhibited following the switch (Allport, Styles et al. 1994). TSI explains the unusual results that sometime occur when a person switches from a more practiced task to a less practiced task; the switch cost is larger in this case than if the same person switches from the more less practiced task to a more practiced task. The larger cost is seen because one must use more effort to inhibit the more practiced task than the less practiced task. Despite the ability to explain this unusual phenomenon, numerous faults have been found with TSI, including cases were there is no evidence of switching time cost when TSI should be present and cases were there is a switch-cost when TSI should not be present (Rubinstein, Meyer et al. 2001).

An alternative theory called Task Set Reconfiguration (Rogers and Monsell 1995) proposes that the switching cost occurs because of short- and long-term costs of the reconfiguration of mental resources to accommodate the new task (Monsell 2003). These reconfiguration costs can include shifting attention between stimulus features, conceptual criteria, goal states, and condition-action rules. The cost of task switching can be mitigated if the person is able to prepare for the switch. The benefit of preparation accrues because some of the task set reconfiguration can take place before the stimulus is presented. Because preparation does not eliminate the switch cost, some of the reconfiguration must be completed after presentation (Rogers and Monsell 1995).

An important determinant of task switching performance is the executive control process, which may consist of two components (Monsell 2003). The first is endogenous control, which depends mainly on the goals of the person and can be completed before the arrival of the stimulus. The second is exogenous control and is triggered by external stimuli in the environment. In the driving domain, the endogenous control might reflect the uncertainty buildup and associated discomfort that occurs when driving tasks are neglected. This process is complemented by exogenous control, which occurs when safety margins are violated and external cues specify dangerous situations, such as the perception of brake lights of the preceding vehicle. Given that switching cost occurs even when a long time is allowed for preparation, it seems that both processes are necessary for task switching.

Most of the research on task switching is at a relatively low, microscopic task level. At this level tasks are simple and last seconds rather than minutes. The level at which actions are defined may have important implications for switching performance and task interruption. Switching between higher level tasks, which are more complex and occur over minutes rather than seconds, may depend on different factors than switching between simple tasks. According to the Action Identification Theory proposed by Vallacher and Wegner (1987) people characterize their actions at different levels of meaning. For example, “drinking coffee” could also be called “getting energized,” “drinking,” or “lifting a cup to my lips.” Action descriptions are organized hierarchically with lower-level actions comprising the high-level actions. For example, “drinking coffee” is a higher-level action description composed of several, more microscopic tasks, such as “lifting a cup.” Action Identification Theory consists of three major principles. The first is that people maintain an action in terms of its prepotent identity, which is used to define the performance criteria and to identify the successful completion of the action. The level at which an action is identified depends on the context in which the action is performed, the difficulty of the action, and the performer’s experience with the action. For example, using a robotic manipulator to guide a coffee cup would likely force a shift in how the action of drinking coffee would be identified. The second principle is that people tend to adopt a higher level of identification when both higher and lower identities are available. The reason for this is that people tend to be sensitive to the larger meanings, effects, and the broader context of their actions. High-level identification lends itself to action stability, in which the person is less likely to engage in other tasks at the same level. The third principle concerns situations in which an action cannot be maintained in terms of its prepotent identity. In these situations there is a tendency for a lower-level identity to become prepotent. This occurs in driving when unexpected events disrupt the ongoing driving activity. For example, poor weather can shift drivers from “going to the store” to “carefully slowing for a stop sign.” IVIS tasks are subject to the same hierarchical classification. Difficulty entering an address in a navigation system may cause the driver to think of the task as “looking for the enter button” whereas before the prepotent action description was “getting directions to Aunt Ida’s house.” The principles of the Action Identification Theory describe qualitative shifts in how the driver views tasks and so may greatly influence how the driver switches between them.

As mentioned in the theory, higher-level descriptions are composed of lower-level descriptions. Goals and tasks are also ordered in a hierarchical manor. For example the task and goal of reading a book can be described and carried out on the levels of words, phrases, sentences, paragraphs, sections, and chapters. If the reader is interrupted, resumption of the reading task will be less effortful if the interruption occurred at the end of a paragraph rather than mid-sentence. Depending on what kind of environmental information triggered the interruption and the urgency of this cue, the reader may be able to postpone addressing the interruption until he or she has reached a more suitable place in the text.

Consistent with the Action Identification Theory, driving activities can be divided into the hierarchical categories of control, maneuvering, and navigation (Michon 1993). Control activities are required to complete maneuvering and maneuvering activities are components of navigation. These categories are sometimes called the operational, tactical, and strategic levels (Koppinen 2000), respectively. Like driving tasks, in-vehicle interactions can also be considered at the control, tactical and strategic levels. Control subtasks of driving, for example, speed control and lateral steering, focus on keeping the vehicle on the appropriate location on the road. Tactical subtasks center on anticipating roadway conditions and consider the vehicle's position in relation to other vehicles and objects and near the roadway. Some examples of this type of subtask include lane choice and selection of appropriate headway. Finally, strategic subtasks of driving involve traveling from one's starting point to the appropriate destination and include route planning and route revision.

These categorizations of driving task are performed with different levels of cognitive control. Rasmussen's SRK model of skill-, rule-, and knowledge-based processing distinctions have been used to describe human performance in a range of domains (Rasmussen 1983). Skill-based processing occurs when the user is very experienced at performing the task and response occurs automatically at a subconscious level. If the user is familiar with the task but does not have extensive experience, cognitive control occurs at the rule-based level of processing. Knowledge-based processing happens when the user is a novice and has not formulated any rules based on task experience. When applied to the driving domain, new drivers perform at the knowledge-based level on all three types of driving activities. As drivers gain driving experience, the control tasks in particular become more automatic and migrate to control at the skill-based level. Maneuvering or tactical driving activities, such as passing, merging, and lane selection, which are not completely automated, probably tend to be performed at the rule-based level of processing. Navigation tasks are less likely to be automatic and so are often completed at the knowledge- or rule-based level.

Since various driving tasks tend to be performed at varying levels of cognitive control, it is likely that the distraction caused by in-vehicle devices will not affect all driving tasks equally. In-vehicle system tasks may affect driving performance at the control level, especially if the system requires vision or manual resources. In-vehicle systems can also affect the tactical level of operation because cognitive resources required for tactical decision making now have to be shared with the system (Koppinen 2000). While some evidence in support of this hypothesis has been found—the GIDS project found that tasks at a high level of driving tend to load more on central resources (Hoedemaeker, de Ridder et al. 2002)—there is a lack of research that addresses the relationship between the attentional demands and different types of driving tasks. Identifying how the types of tasks performed with in-vehicle telematic devices affect driving performance for the different cognitive levels of processing will be crucial to our objective of detecting and mitigating driver distraction.

In addition to monitoring and interpreting information from the environment and switching between tasks, strategic task management also consists of maintaining a list of tasks to be done in a queue and reprioritizing these tasks as needed. According to a study by Moray, Dessouky et al. (1991), in order to successfully manage a queue of tasks, the operator needs to understand the temporal constraints of each task. Research by Woods (1982; cited in Adams, Tenney et al. 1991) revealed four biases that people make when scheduling tasks. In addition to being reluctant to interrupt tasks as mentioned previously, people tended to switch from area to area in a routine order instead of in the most efficient order; delegate tasks to automation in order to reduce the number of areas that they needed to deal with, even though it would have been beneficial for the participants to complete the tasks themselves; and disregard the principle of “time is money.” The tasks used in many dual task experiments are "empty" tasks, whereas the tasks that people perform in real multi-task situations require "thoughtful behavior" to complete successfully and impose real consequences if this goal is not met (Adams, Tenney et al. 1991). Thus, the workload experienced in managing multiple tasks in actual situations can be assumed to be much higher than in experimental settings.

Some important findings from the literature regarding strategic task management include:

- Responses take longer and are less accurate following a switch to a new task
- Advanced knowledge of an upcoming switch reduces (but does not eliminate) the cost of switching
- Task performance recovers quickly after a switch, but there is a long-term performance decrement compared to single-task performance
- Exogenous factors (characteristics of the tasks and their context) interact with endogenous factors (goals and deliberate intentions) to govern how tasks are identified and how people switch between them.
- The task identity can range from a high-level description to a detailed description and this identity guides performance criteria
- People tend to adopt high-level descriptions of tasks when possible
- Breakdowns in task performance lead people to adopt lower-level descriptions
- A hierarchical description of tasks may help identify natural points at which the task can be most easily interrupted.
- Adopting task descriptions on different levels may lead to changes in the level of cognitive control (i.e., skill-, rule-, or knowledge-level) required to perform a task
- Research has shown that people are susceptible to biases which make them non-optimal task schedulers.

5.6 INTEGRATED MODEL OF DISTRACTION

Figure 5.8 shows a preliminary conceptual model that integrates many of the theoretical considerations regarding driver distraction. 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 5.8 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.

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 (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.

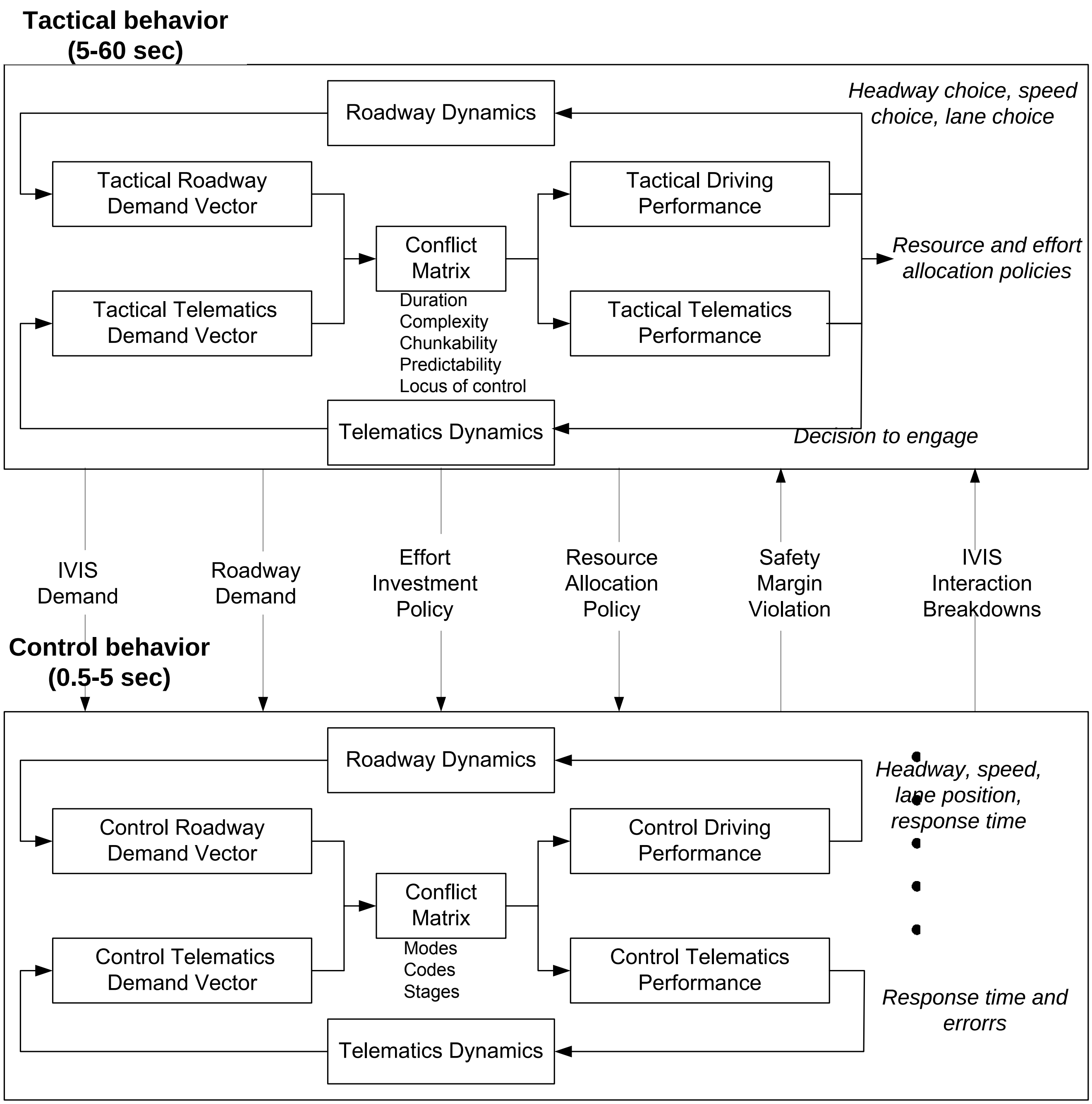

Figure 5.8. Integrated model of distraction, showing the interaction of behavior at the tactical and control levels on driving and IVIS performance.

5.7 MEASURES OF DISTRACTION

Driver distraction is a complex phenomenon that cannot be predicted from a single variable. Instead, predicting driving-related performance decrements requires multiple convergent measures. For predicting cognitive distraction, three main categories of measures have been adopted: physiological, performance, and task demands. The following sections describe criteria for selection measures, representative measures from each category, and considerations for how they might be integrated into a precise estimate of distraction.

5.7.1 Considerations for selecting measures of distraction

A wide range of measures have been used to assess workload and distraction. Many years of research in the area of mental workload provide a useful basis for selecting measures that might be sensitive to high levels of effort—an important element of distraction. The goal of real-time measurement of cognitive distraction with technology that could be incorporated into production vehicles places severe constraints on the potential measures. Specifically, the following four criteria reflect these constraints:

- Timely—the measures must change quickly enough such that any change in measured distraction can be used to preserve driver safety. In other words, the time constant of the measure must be similar to the time constant of the adaptive system and driving situation.

- Diagnostic—the measures must differentiate between different types of distraction, such as attentional withdrawal, underload, and overload. Ideally, measures would even indicate the type of demands facing the driver, such as those defined by MRT.

- Sensitive—the measures must change when the level of distraction changes and should not change in response to irrelevant changes, such as ambient temperature.

- Practical—the sensor and data reduction requirements must be feasible in terms of cost and intrusion on the driver. Drivers are unlikely to pay thousands of dollars for a system that requires them to attach a series of electronic leads to their body each time they drive.

Possible physiological, driver performance, and task demand measures are described according to these criteria and then summarized in Table 5.2 at the end of this section.

5.7.2 Physiological measures of distraction

No one physiological measure can tell the complete story of workload demands and effort. For example, Hankins and Wilson (1998) used multiple measures in order to “provide a comprehensive picture of the mental demands of flight.” They conclude that the “continuous nature of the psychophysiological data may make it possible to develop systems which provide on-line monitoring of mental workload." Physiological measures can be classified into two categories. Measures of emotional and physical activation include measures such as heart rate and pupil size (Hart and Wickens 1990) and are related to general arousal (Gopher and Donchin 1986). Measures such as event related potentials and eye movements reflect mental and perceptual processing (Hart and Wickens 1990) and reflect multiple resource theories (Gopher and Donchin 1986). The first set of measures may be helpful for detecting instances of driver distraction due to underload or attentional withdrawal while the second set is ideal for determining when drivers are overloaded. de Waard (1996) reviews a number of physiological measures that are candidates to measure driver mental workload in his thesis. Physiological measures are objective and cannot be affected by devoting extra effort to a task as performance measures can. Wilson found several different kinds of physiological measures, such as heart rate, heart rate variability, eye blinks, electrodermal activity and brain wave activity to be consistent both between and within pilots who flew the same course on different days.

5.7.2.1 Eye movements and scan patterns

Eye movement data often contain information about saccades, fixations, glances, and scan patterns. Numerous studies have investigated the effect of workload on these eye movements. The results of such studies are consistent in that they show that eye movements are affected across a variety of tasks and workloads, providing promising evidence that eye movement data could provide reliable indications of driver workload. For example, Recarte and Nunes (2000) investigated eye movements made while concurrently driving and performing a secondary task. The secondary tasks consisted of verbal and spatial-imagery tasks. Both types of tasks significantly shrank the area of the driving scene that the drivers scanned, and the spatial task resulted in a significantly smaller scanned area than the verbal task. These results can be seen in Figure 5.9. Participants also drove faster and checked their mirrors and speedometer less often while performing the secondary tasks as compared to driving alone. These results suggest that increased mental workload led drivers to shed the tasks of mirror and instrument scanning. Such shedding may have implications for the driver's awareness of the driving environment and event or change detections.

The tunnel vision-like effect seen during cognitive processing has been researched in both basic and applied settings. Experimental psychology experiments, such as those of Rantanen and Goldberg (1999) who found that cognitive load associated with a counting task influenced the size of the visual field. Under a medium workload, the visual field shrunk, on average, 7.8% and under a heavy workload, almost 13.6%. May, Kennedy et al. (1990) found similar results when they induced workload through a tone counting task. As the complexity of the counting task increased, the length of the saccades decreased significantly.

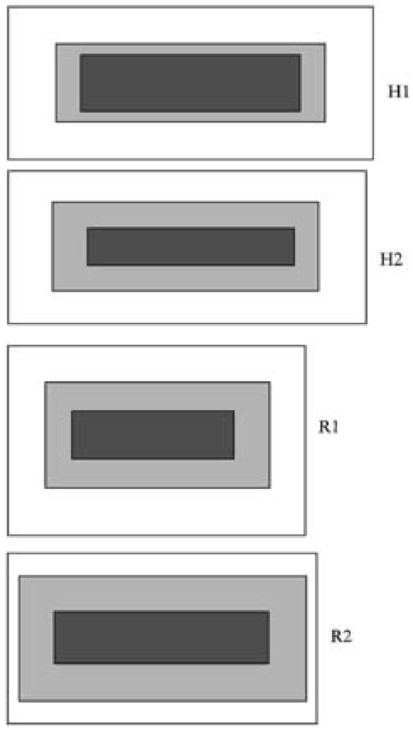

Figure 5.9. Visual inspection windows with no task (white), with verbal task (light gray), and with imagery task (dark gray). H1, H2, R1, and R2 represent the four different roadway conditions (Recarte and Nunes, 2000).

Williams has performed a series of experiments (1982; 1988; 1995) with the goal of answering the question whether the changes in the visual field which occur with increased workload are a true tunnel-vision effect or are more of a generalized nature. If true tunnel-vision occurs, a higher cognitive load will not only have a greater impairment on performance, but this impairment will grow worse as the stimuli are located more eccentrically. Williams (1982) found increased reaction time with higher cognitive load but that this increase was not affected by the eccentricity of the peripheral stimuli. Even though there was a "slight tendency" towards tunnel-vision, overall the data supported the theory of generalized shrinkage of the visual field under increased workload. In a subsequent experiment (Williams 1988), some subjects were instructed to perform the central task as the primary task and to attend seriously to it, while other subjects were instructed to perform both tasks as fast and as accurately as possible. The high cognitive load group which received the central bias instructions showed a tunnel-vision effect, while the other three groups did not.

The findings of an applied study by Sodhi, Reimer, and Llamazares (2002) are complimentary to those of Recarte and Nunes (2000). Sodhi, et al. asked participants complete a number of tasks while driving, including a computation task and a memory task. Analysis of the eye movement data showed a “pronounced” reduction in eye movements for these cognitive tasks in comparison to “glance” tasks that required the driver to look away from the roadway. The author's also noted, "The driver's eyes 'wander' around the center of the forward view." The results also indicated that this reduction in eye movements did not end when the task ended, confirming the findings of Redelmeier and Tibshirani (1997).

Other studies have revealed that driver experience seems to affect scanning behavior as measured by fixation length. For example, Crundall and Underwood (1998) found that while experienced drivers increased the length of their fixations on the least demanding roadway, inexperienced drivers increased fixation duration on a more demanding roadway. One explanation the authors present for the findings is that experienced drivers may reduce fixation duration in order to compensate for the additional demand of driving in a more complex environment. Novice drivers may not have developed this strategy. Another study involving experienced and inexperienced drivers (Unema and Rotting 1988) found decreased fixation duration with increased situation complexity. However, the more experienced the driver, "fixations of extreme short duration occur less." In addition, the data suggest that "there exists a link between the control of fixations of extreme short durations and the energetic state of the subject."

5.7.2.2 Endogenous eye blinks

Endogenous eye blinks, unlike eye blinks provoked by events in the visual scene or loud noises, occur without an identifiable eliciting stimulus and may be a useful measure of cognitive load. Eye blinks are described in terms of rate, duration, and latency. Eye blink rate, which is the blink characteristic that has been studied the most (Kramer 1991), has been shown to increase with fatigue, and higher task demand leads to decreases in duration. These eye blinks can be measured through video analysis, corneal reflection, or with an electrooculogram (EOG), which is more accurate than video when measuring duration (Wilson and Eggemeier 1991; cited in de Waard 1996). However, EOG requires the placement of skin electrodes near the eye and corneal reflection requires the subject to remain still (Kramer 1991) so all three methods are less than ideal for practical application in vehicles. While a recent study found that blink rate closely paralleled changes in roadway curvature—as the radius of curvature decreased, the blink rate increased (Richter, Wagner et al. 1998)—other studies on eye blink rate have produced conflicting results and so more research is needed (Kramer 1991). While both blink latency and duration are sensitive to information processing and workload, they are sensitive in a global rather than specific manner (Kramer 1991). In addition, other factors, such as air quality (de Waard 1996) and fatigue (Kramer 1991) can affect blink behavior.

5.7.2.3 Pupil dilation

Kahneman (1973), who proposed pupil diameter as a measure of mental workload, found that increased processing demands and resource investment led to increases in pupil diameter. Beatty (1982) also found that pupil diameter accurately reflects cognitive load. Pupillary response has been found to be "related to information-processing" (Backs and Walrath 1992; cited in de Waard 1996), mental processing load (Hoeks 1995; and Hyona, Tommola et al. 1995; cited in de Waard 1996), and fatigue

(Murata 1997; Morad, Lemberg et al. 2000). However, Kramer (1991) does not consider pupil diameter to be very diagnostic since it has shown sensitivity to a wide range of processing demands. Pupil diameter is also sensitive to factors unrelated to task demand, such as changes in the ambient light levels, emotional state, and pupil constriction in order to focus on a distant target.

5.7.2.4 Cardiac measures

The electrocardiogram data can be analyzed in the time domain or with frequency analysis. Time domain measures include heart rate, inter-beat-interval, and heart period. Roscoe (1992; cited in de Waard 1996) found that in the absence of physical effort, heart rate was affected most by workload. Veltman and Gaillard (1998) found heart period to be sensitive to differences in task demand for pilots performing a simulated tunnel navigation task. In addition to physical effort, heart rate is also affected by emotion, speech production, sedative drugs, and fatigue (de Waard 1996).

Frequency analysis of cardiac data involves dividing heart rate variability into various frequency bands. The low frequency band consists of 0.02-0.06 Hz and has been linked to the regulation of body temperature. The mid-range consists of 0.07-0.14 Hz and is related to short-term blood pressure regulation. The high band (0.15-0.50 Hz) reflects respiratory fluctuation. The mid- and high bands range, also called the 0.10 Hz component, reflect changes in mental effort (de Waard 1996). Wilson (2002) found that heart rate variability was less sensitive to task demands on pilots than heart rate. Veltman and Gaillard (1998) found that only large changes in task difficulty were reflected in heart rate variability measures. Althaus and Mulder (1998) found that the frequency band which best reflected changes in task load depended on each participant’s breathing pattern. Researchers have found a range of heart rate measures to be sensitive to various types of task load, but the decrease in 0.1 Hz variability has been shown to be particularly sensitive and diagnostic to cognitive effort (Mulder 1992).

The brainstem plays an important role in regulating behavior and physiological reactivity to stress. Comprised of parasympathetic (growth and restoration) and sympathetic (increased metabolic output to deal with challenges external to the body) nervous systems, the autonomic nervous system regulates internal environment of body to maintain homeostasis. The two systems work in tandem and usually in opposite directions. Autonomic responses to external stimuli (say pain or attention) produce a decrease in parasympathetic tone. Such withdrawal in response to a challenge may define stress. One physiological measure that can be used to diagnose such a decrease in the parasympathetic tone is the vagal tone. Vagal tone is derived from heart rate pattern detected by electrocardiogram and the period between heart beats must be timed with millisecond accuracy. Then this data is processed with a patented method which includes the application of time domain filters (Porges 1995). Vagal tone reflects stress, which can be a result of high mental workload or other factors such as the driver’s emotional state.

In addition to the challenge of gaining access to the heart beat rhythm through electrodes of some sort, some common diseases such as hypertension or diabetes are characterized by a depression of parasympathetic tone (Porges 1995) that would make changes difficult or impossible to detect. Also unknown is the amount of stress or excitation required to illicit a detectable response.

5.7.2.5 Respiration

Respiration rate has been shown to increase under stressful attention conditions, increased memory load, and increased temporal demands (Backs and Ryan 1992; Porges and Byrne 1992; and Backs and Seljos 1994; cited in de Waard 1996). Other studies have shown that increased cognitive activity results in decreased respiration rate. Another respiration measure is tidal volume. When respiration rate is multiplied by tidal volume, the result is minute ventilation or the quantity of air breathed per minute. A major challenge in using respiration to estimate workload is how to measure it. All accurate methods (e.g., flow meters) are highly intrusive and sometimes require calibration, while less intrusive measures (e.g., strain gauges) are also less accurate. In addition to measurement difficulties, respiration is obviously not uniquely sensitive to mental effort, as physical effort, speech production, and emotion also have significant effect on respiration. Decreases in respiration rate coincide with increases in cognitive activity (de Waard 1996).

5.7.2.6 Blood Pressure

Blood pressure variability is “closely related” to heart rate variability (de Waard 1996) and has been shown to reflect mental load (vanRoon, Mulder et al. 1995). In order to capture blood pressure variability, measurements must be made continuously, usually through the use of finger cuff (de Waard 1996). However, this technique may be somewhat intrusive and impractical for a production vehicle.

5.7.2.7 Electrodermal activity

The electrical changes that occur in the skin are called electrodermal activity (EDA) and are most commonly measured using an external source of a small electrical current. The measurements are usually made on the palm of the hand or sole of the foot. The average or baseline level of EDA is called the tonic EDA, and the phasic or time-varying EDA measures include the electrodermal response (EDR) which is similar to galvanic skin response and expressed as Skin Conduction Response (SCR). EDR measures have a slow response with a latency of over one second and electrodermal activity measures are globally sensitive to any behavior that affects the sympathetic nervous system. Ambient temperature and humidity can also affect these measures making them somewhat impractical in a production vehicle (de Waard 1996).

5.7.2.8 Electroencephalogram

An electroencephalogram (EEG) measures electrical activity by placing electrodes on the scalp. EEG signals are classified into four different bands: delta (up to 4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (>13 Hz). The use of EEG as a measurement of mental workload research is rare (de Waard 1996). In the few studies that have been completed, activity in the alpha band decreased and activity in the theta band increased during dual-task performance as compared to single-task performance (Sirevaag, Kramer et al. 1988; cited in de Waard 1996). EEG is more commonly used to assess arousal in studies of operator vigilance (de Waard 1996) and for this reason might be useful in determining when a driver has withdrawn attention or is underloaded. However, the instrumentation requirements are intense and are incompatible with the driving environment.

5.7.2.9 Event Related Potential

Event related potential refers to time-based changes in electrical activity of the brain in response to particular events, rather than the global activity reflected in the EEG measures. The most common ERP measure is the P_{300}, which refers to a change in "amplitude and latency of positive potentials that occur minimally 300 ms after stimulus presentation" (de Waard 1996). Unexpected stimuli that are task-relevant cause increases in P_{300} amplitude and there is evidence that P_{300} latency reflects the cognitive-evaluation time associated with the information processing requirements of a task and increases with task complexity (Kramer, Trejo et al. 1995; Garcia-Larrea, Perchet et al. 2001). Gopher and Donchin (1986; cited in de Waard 1996) found the P_{300} to reflect the perceptual/central processing load before performance declines. When both a primary and a secondary task are being performed concurrently, the P_{300} amplitude decreases as primary task difficulty or priority increases (Kramer 1991). In the irrelevant probe method, which eliminates the need for a secondary task, the participant hears irrelevant tones that s/he is instructed to ignore. If task load is low, the participant has spare capacity to process the irrelevant stimuli. As task difficulty increases, ERP amplitude decreases. However, this method assumes that the spare capacity will be allotted to the processing of the irrelevant stimuli and not to some other cognitive task (Kramer 1991). All ERP techniques are affected by signal noise and intra-individual variability (de Waard 1996). Like EEG measures, the instrumentation requirements are intense and incompatible with the driving environment.

5.7.2.10 Hormone levels

Certain hormones such as adrenaline, noradrenaline, and especially cortisol are indicators of stress. Analysis of hormone levels can separately identify physical and mental workload. However, urine, blood, or saliva sampling is required for and the result reflects accumulated stress levels (de Waard 1996). Therefore, it is quite difficult to relate changes in hormone levels to distractions in a way that could guide an adaptive system. The timeliness and practicality of these measures is a problem for implementation in a production vehicle.

5.7.2.11 Electromyogram

The measurement of the electrical activity in the facial muscles is called electromyography or EMG. The tonic activity of the lateral frontalis muscle, the corrugator supercilii, and the orbicularis oris inferior reflect mental effort and the use of general resources while the orbicularis oculi, zygomaticus major, and temporalis muscles are less or not sensitive to mental effort (de Waard 1996). “Activity of the orbicularis oculi and zygomaticus major ‘may be representative of situation where suboptimal performance can no longer be compensated for by the mobilization of additional resources” (Van Boxtel and Jessurun 1993; cited in de Waard 1996). Electromyograms can be contaminated by emotion and might also be confounded with speech activity. In addition, collecting these data requires the application of electrical leads on the driver’s face and is not practical to implement in vehicles; however, sophisticated image processing might be able to extract some of the same information less intrusively.

5.7.3 Driving performance

There are a variety of driver performance measurements and some may be useful indicators of distraction. A review of driver performance measures includes the following as major categories (Wierwille, Tijerina et al. 1996):

- Lateral control measures, including lane-related measures, steering-related measures, heading and lateral-acceleration measures
- Longitudinal control measures, including accelerator-related measures, brake/deceleration-related measures, speed-related measures, and vehicle following-related measures
- Obstacle and event detection, including probability of detection measures and detection latency measures
- Driver response measures to presented stimuli
- Vision-related measures, including allocation to roadway and to in-vehicle controls and displays
- Manual-related measures, including hands-on wheel frequency, duration, and total time.

A benefit of most driver performance measures is that they are easily measured and are not intrusive. Unfortunately, speed and lane position control may not be sensitive to low levels of distraction. Headway maintenance, especially driver reaction time to lead vehicle deceleration, is more sensitive to cognitive distraction. The major drawback of driver performance measures is that they are lagging indicators of distraction and reflect the negative results of distraction. On the other hand, driver performance measures have been shown to be indicative of the specific ways in which distraction affects driver performance. Young and Angell (2003) demonstrated that driver performance measures could be combined using Principle Component Analysis. Three principle components accounted for 83% of the variability in the fifteen driver performance measures. Based on the composition of these three principle components in terms of the performance variables, the components were interpreted as “overall driver demand,” “low-workload-but-high-inattentiveness,” and “peripheral insensitivity.” These results suggest that the effects of distraction are more complicated than what can be captured in a single measure such as brake reaction time.

5.7.4 IVIS interaction

The driver's interaction with the IVIS might provide a useful basis to estimate distraction. Knowing what IVIS functions have been engaged and when the driver is pressing buttons or issuing commands could be a very precise and timely estimate of distraction. The primary challenge is to relate the IVIS state and the history of IVIS state transitions to the level of driver distraction. For example, knowing the cellular phone is on does not indicate how engaging the conversation is. Because a one-to-one mapping between IVIS state and driver distraction does not exist, some form of model or lookup table is needed to estimate distraction. One promising approach is the multiple resource model discussed earlier. This approach can describe driving demand and IVIS task demands in terms of a vector of resource requirements. The conflict in these resource requirements represents the performance decrement that can be expected in the driving and IVIS tasks. Similarly, the ACT-R model has been successfully applied to estimate cognitive distraction (Salvucci 2002). The ACT-R approach decomposes the IVIS interaction into a series of production rules and elemental cognitive tasks. Another approach, the OFM-COG framework, uses a set of high-level task descriptions to identify the information processing resources they demand. This approach has been used to define IVIS functions (Lee, Kantowitz et al. 1994; Lee, Morgan et al. 1997) and to estimate their cognitive demands (Hankey, Dingus et al. 2000). This description may be particularly useful in addressing the factors affecting the decision to engage in in-vehicle task and the tendency for some in-vehicle tasks to preempt driving tasks. Table 5.1 shows sets of terms that describe generic cognitive tasks that in turn can be used to describe a range of IVIS interactions. These task descriptions might provide a useful method of describing IVIS demands at the tactical level. High levels of IVIS demand would be characterized by interactions that demand multiple cognitive tasks shown in Table 5.1. The right column of Table 5.1 shows the information processing resources demanded by each cognitive task and so may be a rough index of individual task demand.

Table 5.1. Tasks from the OFM-COG framework for estimating cognitive demands of human-system interactions (Lee and Sanquist 2000).

Cognitive Task	General Category of Information Processing	Information Processing Resources
1. *Input select.* Selecting what to pay attention to next.	Acquisition	Selective attention, Perceptual sensitivity
2. *Filter.* Straining out what does not matter.	Acquisition	Selective attention
3. *Detect.* Is something there?	Acquisition	Perceptual sensitivity, Distributed attention
4. *Search.* Looking for something.	Acquisition	Sustained attention, Perceptual sensitivity

Cognitive Task	General Category of Information Processing	Information Processing Resources
5. *Identify.* What is it and what is its name?	Acquisition/Interpret	Perceptual discrimination, Long-term memory, Working memory
6. *Message.* A collection of symbols sent as a meaningful statement.	Handling	Response precision
7. *Queue to channel.* Lining up to process in the future.	Handling	Working memory, Processing strategies
8. *Code.* Translating the same thing from one form to another.	Handling	Response precision, Working memory, Long-term memory
9. *Transmit.* Moving something from one place to another.	Handling	Response precision
10. *Store.* Keeping something intact for future use.	Handling	Working memory, Long-term memory
11. *Store in Buffer.* Holding something temporarily.	Handling	Working memory, Processing strategies
12. *Compute.* Figuring out a logical or mathematical answer to a defined problem.	Handling	Processing strategies, Working memory
13. *Edit.* Arranging or correcting things according to rules.	Handling	Long-term memory, Selective attention
14. *Display.* Showing something that makes sense.	Handling	Response precision
15. *Purge.* Getting rid of the irrelevant data.	Handling	Selective attention
16. *Reset.* Getting ready for some different action.	Handling	Selective attention, Response precision
17. *Count.* Keeping track of how many.	Handling/Interpretation	Sustained attention, Working memory
18. *Control.* Changing an action according to plan.	Handling/Interpretation	Response precision
19. *Decide/Select.* Choosing a response to fit the situation.	Interpret	Long-term memory, Processing strategy
20. *Plan.* Matching resources in time to expectations.	Interpret	Working memory, Processing strategy
21. *Test.* Is it what is should be?	Interpret	Perceptual sensitivity, Working memory, Long-term memory
22. *Interpret.* What does it mean?	Interpretation	Long-term memory, Sustained attention

Cognitive Task	General Category of Information Processing	Information Processing Resources
23. *Categorize.* Defining and naming a group of things.	Interpretation	Long-term memory, Perceptual sensitivity
24. *Adapt/Learn.* Making and remembering new responses to a learned situation.	Interpretation	Long-term memory
25. *Goal image.* A picture of a task well done.	Interpretation	Long-term memory, Processing strategies

Blanco (1999) described tasks using a scheme similar to that in Table 5.1. In her study, participants performed normal driving in an instrumented vehicle while performing various tasks with both visual and auditory IVIS displays. The visual tasks were characterized as (1) search, (2) search-compute, (3) search-plan, (4) search-plan-compute, (5) search-plan-interpret, and (6) search-plan-interpret-compute. The IVIS displays varied in presentation format and number of decision alternatives. The auditory tasks, which had two levels of density, were categorized as (1) listen, (2) listen-plan, (3) listen-compute, and (4) listen-plan-compute. Five conventional in-vehicle tasks (activate turn signal, adjust mirror, etc.) were also completed. The participants were allowed to skip a task if they felt they could not complete it safely. In addition, the ride-along experimenter was allowed to skip tasks if the participant had skipped or had difficultly performing a less complicated task. The results showed that tasks involving decision making components, both visual and auditory, were much more likely to be skipped, led to more "erratic" driving, and required more eyes-off-road time.

Using the history of IVIS interactions to estimate distraction is quite promising, but several challenges confront this approach. First, these models are limited regarding how they account for task scheduling and strategic task management. This makes any extrapolation regarding what a driver is doing with information extracted during the last IVIS interaction problematic. In addition, these models assume a driver engages in a specific well-defined strategy in performing a task. For example, MRT might assume that interpreting navigation information loads heavily on spatial resources; however, some drivers might adopt a strategy that involves primarily verbal resources. Differences in the choice of a strategy between and within individuals over time might be substantial. Finally, practical application of these models assumes that the cognitive demand associated with IVIS interactions can be efficiently and reliably linked to the IVIS state information. Using IVIS state information to estimate IVIS demands requires substantial expert judgment and makes it impossible to create a standard that third party developers could use to describe IVIS interactions. Although using the history of IVIS interaction to predict cognitive load has important limits it is uniquely suited to provide predictive information regarding future levels of driver distraction.

5.7.5 Measure interactions

Table 5.2 shows that no one method perfectly satisfies all the criteria for estimating cognitive distraction. Each measure has a different profile of strengths and weaknesses. Of the physiological measures, the most promising alternatives include: eye movements, eye blinks, and the 0.1 Hz measure of heart rate variability. Eye blink and pupil dilation are particularly problematic with respect to sensitivity. Many factors unrelated to workload affect these measures; however, the same hardware used to collect eye movement might also be used to collect eye blink and pupil dilation data. The most promising driver performance measures are those associated with lane keeping and headway maintenance. Of the cognitive models, the MRT and OFM-COG provide complementary descriptions of cognitive demand. Using all of these measures to estimate driver distraction has the benefit that the limits of one are compensated by another. Another benefit is that the interactions between them may lead to new insights regarding distraction. For example, eye movements are systematically related to lane position control (Land and Lee 1994) and lane change behavior (Hildreth, Beusmans et al. 2000). Breakdowns in these relationships may be more sensitive to distraction than an univariate analysis of either steering behavior or eye movement. Similarly, physiological and driver performance variables could be used to disambiguate and tune the models for estimating driver distraction as a function of IVIS interactions.

Table 5.2. Summary of potential measures to estimate cognitive distraction, with the most promising highlighted in bold.

Measure	**Timely**	**Diagnostic**	**Sensitive**	**Practical**
Eye movements and scan patterns	●	●	●	□
Endogenous eye blinks	●	□	○	□
Pupil dilation	●	○	○	□
Cardiac measure—0.1 Hz variability	□	●	●	□
Cardiac measure—Vagal tone	□	□	□	○
Respiration rate	●	□	○	○
Blood pressure	□	●	●	○
Electrodermal activity	○	□	○	○
Electroencelphalogram (EEG)	●	●	●	○
Event related potential (ERP)	●	●	●	○
Hormone levels	○	□	○	○
Facial electromyography (EMG)	●	□	□	○
Driving performance—Lane position	□	□	□	□
Driving performance—Speed control	□	○	□	●
Driving performance—Headway maintenance	□	□	●	●
IVIS interactions—MRT-based estimation	●	□	□	□
IVIS interactions—ACT_R-based estimation	●	□	□	□
IVIS interactions—OFM-COG-based estimation	●	□	□	□

● = Very appropriate
□ = Somewhat appropriate
○ = Inappropriate

5.8 ALGORITHMS FOR PREDICTING DISTRACTION

The overall objective of this project is to combine the various measures of distraction to predict increased reaction time to unexpected roadway events. The most common and simple way to achieve this goal is to construct a linear model using linear regression techniques. This approach has been shown to be robust in many decision making situations (Dawes and Corrigan 1974); however, such an approach may not extract as much information as other techniques. Specifically, Hidden Markov Models and Support Vector Machines provide qualitatively different approaches to data reduction and prediction and do not depend on the same assumptions of linear regression.

5.8.1 Hidden Markov models

Hidden Markov Models (HMMs), proposed by Baum and his colleagues (Baum and Petrie 1966; Baum and Egon 1967; Baum and Sell 1968; Baum, Petrie et al. 1970; Baum 1972), represent stochastic sequences as Markov chains where the states are not directly observed but are associated with a probability density function (Rabiner and Juang 1986). HMMs are a doubly stochastic process with an underlying stochastic process that is not directly observed. However, the underlying stochastic process can be exposed through another set of stochastic processes that produce the sequence of observed symbols (Rabiner and Juang 1986; Rabiner 1989). These models help to both characterize and explain data output sequences through modeling techniques. HMMs were first implemented in speech recognition and processing research. However, recently they have been employed in other venues such as simulation modeling, eye movement modeling, and show promise in the current project to detect driver distraction. Salvucci (1999; 2000) used HMMs to create an aid that attempts to increase the reliability of typing using eye fixations by implementing HMM modeling to more robustly determine the letters being typed. In another study HMMs were used to estimate hidden task transitions made by pilots during flight simulation (Hayashi, Oman et al. 2003). HMMs seem to be a promising method to detect varying levels of distraction while driving. As data output is generated, the observations will be compared to the HMM distraction models. The model that best fits the observation data will be determined, using the set of algorithms described below, and will indicate the level of driver distraction.

The underlying mechanisms behind the implementation of HMMs are that there are a finite number of states (N) in a particular HMM. At each iteration a new state is entered based on a predefined transition matrix. The transition may either be from state to state or may be a transition within the same state. Following each transition an observation output is produced based on the probability distribution of the current state (Rabiner and Juang 1986). These observation outputs are then compared to the observation sequences and the HMM that best describes the observation sequences is determined.

Descriptions of the variables of interest include:

$$Q = \text{the set of states} = \{q_1, q_2, ..., q_n\}$$
$$V = \text{the output alphabet} = \{v_1, v_2, ..., v_n\}$$
$$\pi(i) = \text{probability of being in state } q_i \text{ at time } t = 0$$
$$\text{(ie, in initial states)}$$
$$\mathrm{A} = \text{transition probabilities} = \{a_{ij}\},$$
$$\text{where } a_{ij} = \Pr[\text{entering state } q_j \text{ at time } t+1 \,|\, \text{in state } q_i \text{ at time } t]$$
$$B = \text{output probabilities} = \{b_j(k),$$
$$\text{where } b_j(k) = \Pr[\text{producing } v_k \text{ at time } t \,|\, \text{in state } q_j \text{ at time } t]$$

A set of three questions must be answered for the model to be used in real world applications (Rabiner 1989).

- Given the observation sequence (O) and the HMM (λ), what is the probability of the given sequence?

$$\Pr(O \,|\, \lambda) = \sum \Pr(O \,|\, I, \lambda) \Pr(I, \lambda) \text{, for all I}$$

$$= \sum \prod {}_{i1} b_{i1}(O) a_{i1} b_{i2}(O) ... a_{iT-1i} b_{iT}(O_T)$$

- Given the observation sequence (O), which state sequence is optimal (Q)?

$$\Pr(i_t = q_i \,|\, O, \lambda) = \frac{\alpha_t(i)\beta_t(i)}{\Pr(O \,|\, \lambda)}$$

- Which HMM model maximizes the observed sequence of data?

$$\Pr(I_t = q_i, i_{t+1} = q_j \,|\, O, \lambda)$$

$$= \frac{\alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)}{\Pr(O \,|\, \lambda)}$$

In practice, the first question can be answered using the Forward-Backward algorithm, the second question can be answered using the Viterbi algorithm, and the final question can be answered using the Baum-Welch algorithm. To verify the effectiveness of the model, observation sequences with known distraction levels will be input and the resulting output will be analyzed.

There are many advantages and limitations to using HMMs. Some of the advantages are that (Rabiner and Juang 1986):

- HMMs can be used to model both discrete and continuous outputs
- HMMs are dynamic and can produce outputs over time
- HMMs are efficient both in memory and run-time
- HMMs are straight-forward in a conceptual manner
- HMMs can be easily implemented using a Matlab toolbox

Some of the disadvantages are that:

- Varying assumptions on the form of observation density can affect the robustness of the model
- It may be fairly difficult to implement HMM pattern recognition in real-time data acquisition

HMMs have yet to be used to model driver distraction. However, eye movement data such as fixation duration, saccade length, and saccade speed have been measured to gauge driver distraction. In addition, HMMs have been used to analyze eye movement data. As a result, using HMM analysis in combination with eye fixation data output to monitor driver distraction in real-time appears to be promising.

5.8.2 Support Vector Machines

Support Vector Machines (SVMs), proposed by Vapnik (1995), are based on the statistical learning technique and can be used as pattern classifiers. Unlike traditional learning methods (e.g., neural networks), which minimize the empirical training error (empirical risk), SVMs and other statistical learning machines aim at minimizing the upper bound of the generalization error (Amari and Wu 1999), also know as the expected risk, which is the reason why they may give more correct results than the traditional methods. From an early study, SVMs demonstrated the ability to generalize well even in high dimensional spaces under small training sample conditions (Jonsson, Kittler et al. 2002) and have been shown to be superior to the traditional methods (Byun and Lee 2002). SVMs have been successfully applied to a number of applications ranging from detection, verification, and recognition of faces, objects, handwritten characters and digits, text, speech and speakers, and retrieval and prediction of information and images (Byun and Lee 2002). SVM is reasonable to use in recognizing the different patterns of eye movements which indicate the status of attention distraction while driving.

The Support Vector Machine algorithm contains several steps. First the training data (binary-class data shown in Figure 5.10 as circles and dots) is mapped according to the following equation:

$$D = \{(x_i, y_i)\}_{i=1}^{l}, x_i \in X \subset R^d, y_i \in Y = \{-1, +1\}$$

into the high-dimensional feature space via $\Phi(x)$. Then a separating hyperplane with maximum margin (the straight continuous line in the feature space in Figure 5.10) is constructed, which ensures the minimization of the generalization error. This yields a nonlinear decision boundary (the continuous curve in input space in Figure 5.10) (Byun and Lee 2002).

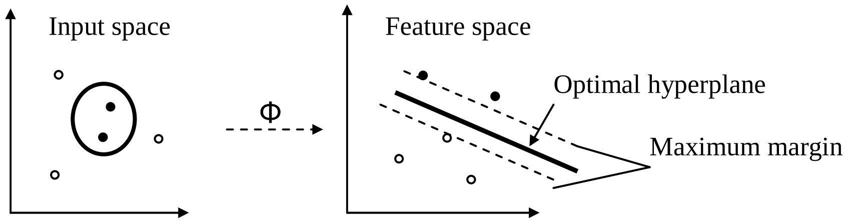

Figure 5.10. Conceptualization of the support vector machine algorithm (Byun and Lee 2002).

In practice, SVMs minimize the function *I* (Barla, Fanceschi et al. 2002; Neelanjan and Mukherjee 2002), called the expected risk. It is the upper bound of the generalization error.

$$I[f] = \frac{1}{l}\sum_{i=1}^{l} V\left(f(x_i), y_i\right) + \lambda \|f\|_K^2$$

f is the trained machine, which is trained by learning the mapping $x_i \mapsto y_i$ (Burges 1998). *V* is a loss function measuring the fit of the function *f* to the training data, which is called "empirical risk." $\|f\|_K$ is the norm of *f* in the feature space induced by a certain positive kernel function *K*, and $\lambda > 0$ is a regularization parameter quantifying the willingness to trade off accuracy of classification with the small norm in the feature space. For several choices of the loss function *V,* minimizing the function *I* takes the general form

$$\sum_{i=1}^{l} \alpha_i K(x, x_i),$$

where the coefficients α_i depend on the examples. The mathematical requirement of *K* must ensure the convexity of the function *I* and hence the uniqueness of the minimum function above.

For SVMs for binary classification, corresponding *V* is like

$$V\left(f(x_i), y_i\right) = \left|1 - y_i f(x_i)\right|_+,$$

with $|t|_+ = t$ if t > 0, and 0 otherwise and leads to a convex quadratic programming problem with linear constraints in which many of the α_i vanish. The points x_i for which $\alpha_i \neq 0$ are termed support vectors and are the only examples needed to determine the solution (Barla, Fanceschi et al. 2002). The function *I* can be seen as the sort of upper generalization error to measuring the validation of SVM. We also can use the test data to evaluate the prediction of SVM.

Some of the benefits of SVMs are that:

- By minimizing the upper bound of the generalization error (or the expected risk), SVMs initially obtain more correct results, in most cases, than traditional methods which minimize empirical risk. In the study of Neelanjan and Mukherjee (2002), the SVM results are at least as accurate as those of neural networks and HMMs (Hidden Markov Models).
- SVMs generalize well even in high dimensional spaces with small training datasets,

Some of the limitations of SVMs, as described by Byun and Lee (2002), are:

- The choice of kernels tends to be difficult as there are no theories concerning how to choose good kernel function in a data-dependent way (Amari and Wu 1999).
- In terms of running time, SVMs are slower than other neural networks for a similar generalization performance (Haykin 1999). Training for very large datasets with millions of support vectors is an unsolved problem (Burges 1998).
- The selection of support vectors is another difficult problem, particularly when the patterns to be classified are non-separable and the training data are noisy. In general, attempts to remove known errors from the data before training or to remove them from the expansion after training will not give the same optimal hyperplane because the errors are needed for penalizing non-separability (Haykin 1999).
- The use of SVM methods for multi-class SVM classifiers require exponentially more resources and are much more difficult to implement when compared to a binary classifier. Although some research has been done, the work for multi-class SVM is an area for future research (Burges 1998).

Despite the limitations of SVMs, the benefit of a more accurate model may be worthwhile. Additional research to investigate the possibility of using SVM to model distraction based on eye movement data and possibly other data, such as driving performance, merits consideration.

5.9 POTENTIAL EXPERIMENTS

5.9.1 Distraction prediction

The objective of the distraction prediction experiment is to identify an equation to predict decrements in reaction time and to assess whether predictors of distraction associated with tactical and control levels of behavior differ. MRT and OFM-COG will be used to define a set of eight different IVIS tasks and drivers will perform these tasks in driving situations that demand different levels of control and tactical performance. Situations that demand high levels of tactical performance are those in which the driver can anticipate the braking behavior of the lead vehicle. Demand vectors and conflict matrices described in Figure 5.8 will be used to predict the differential effects of the IVIS tasks on tactical and control performance. The specific independent variables include:

- IVIS demands (Spatial/Verbal, Perceptual/Response Selection, and Complex/Simple response)
- Driving control demands (response to the random braking of a lead vehicle) and tactical demands (response to the braking of a lead vehicle that is cued by other events, such as a traffic light changing from green to red)

Specific outcomes of the experiment include:

- The degree to which IVIS interactions, physiological, and driving performance measures, alone and in combination, can predict reaction time decrements
- The extent to which distraction affecting tactical performance displays a different signature compared to distraction affecting control performance
- The difference between individual and generic models in their prediction of distraction
- The relative robustness, reliability, and specificity of traditional linear regression, Hidden Markov Models, and Support Vector Machines in predicting driver distraction

5.9.2 Task management assessment

The objective of the task management assessment experiment is to investigate the factors that influence the driver's ability to effectively switch between driving and an in-vehicle task. Figure 5.8 describes the relationship between tactical decisions, such as the decision to engage and the characteristics of the IVIS. This experiment will investigate several of these factors to identify potential distraction mitigation strategies that go beyond those associated with avoiding distraction related to overload. Specifically, this experiment will investigate factors influencing drivers' judgments regarding when to engage in IVIS tasks and when to suspend interaction with IVIS tasks. As part of this effort the experiment will also investigate the dynamics of distraction, with the hypothesis that longer tasks will result in a gradual withdrawal of attention from the roadway. Specific independent variables include:

- Roadway demand (rural curves, rural straight, suburban)

- Duration of IVIS tasks
- Whether cue to start an IVIS tasks is endogenous (based on the driver's inclination) or exogenous (alert from the system)

The specific outcomes of the experiment include:

- The degree to which IVIS task duration affects driving performance and the decision to remain engaged in the IVIS task
- The degree to which endogenous and exogenous cues affect the decision to engage
- The ability of various distraction measures (e.g., eye movements, heart rate variability) to reflect decrements in driving performance associated with the potential withdrawal of attention that may occur as driver complete long IVIS tasks

5.10 CONCLUSION

A great range of technology may enter passenger vehicles in the near future. This is likely to pose distractions considerably greater and more varied than those currently posed by cellular phones, CD players, and climate controls. Longer commute times and increased productivity pressures may encourage drivers to use these devices. To mitigate the distraction associated with these devices, distraction can be measured in real time and used to adapt the IVIS. To achieve this objective this report reviewed literature related to previous efforts to develop adaptive automation, distraction and workload, the underlying theoretical basis of multitask performance, measurement techniques, and data integration and analysis algorithms. Literature from each of these areas offers useful guidance for estimating driver distraction.

Regarding previous efforts to produce adaptive automation and driver support systems, the following primary conclusions emerge:

- Driver characteristics such as age and level of experience, both with the driving and the various IVISs and IVIS functions, can guide adaptation.
- Driver adaptation to the IVISs, such that the safety benefits are eroded as drivers take advantage of the increased ability to do non-driving tasks as they drive, should be assessed in developing adaptive systems.
- Driver-specific models for detecting and mitigating distraction may be substantially more effective than generic models.
- Driver variables should be monitored for signs of both overload and underload, particularly as vehicle automation (e.g., adaptive cruise control) reduces drivers' vehicle control interactions.
- The demands of the IVIS, including the types of tasks and the modality in which the tasks are conveyed influence driver workload.
- The extent to which the IVIS devices are integrated (e.g., consistent interface features, minimization of data entry, coordination and prioritization of messages) has important implications for the cognitive demand they impose on the driver.
- Driver acceptance of system adaptation strategies is critical so that the system will not be subject to misuse or abuse.

Regarding previous research addressing workload, the following primary conclusions emerge:

- Workload depends on multiple aspects of the task (e.g., visual, manual, and cognitive components).
- Both the roadway environment and the in-vehicle system contribute to the demands that confront the driver.
- Control strategies and performance criteria greatly influence the amount of effort expended and workload experienced by the driver.
- Withdrawal of effort from driving tasks and focus on IVIS can degrade safety without any indication of information overload.

- Conditions of underload can lead to distraction-related performance decrements, particularly during transitions from underload to overload.

Regarding research addressing task management and task switching, the following primary conclusions emerge:

- Responses take longer and are less accurate following a switch to a new task.
- Advanced knowledge of an upcoming switch reduces the cost of switching.
- Advanced knowledge does not eliminate the cost of switching.
- Task performance recovers quickly after a switch, but there is a long-term performance decrement compared to single task performance.
- Exogenous factors (characteristics of the tasks and their context) interact with endogenous factors (goals and deliberate intentions) to govern how tasks are identified and how people switch between them.
- The task identify can range from a high-level description to a detailed description, and this identify guides performance criteria.
- People tend to adopt high-level descriptions of tasks when possible.
- Breakdowns in task performance lead people to adopt lower-level descriptions.
- Driving consists of three qualitatively different levels of behavior: strategic, tactical, and control behavior. Distraction may affect each of these behaviors, but most research has addressed only control behavior.

Conclusions regarding adaptive automation, workload and task management guide the development of methods to estimate driver distraction. Most fundamentally, distraction can best be estimated by multiple means. Specifically, data regarding driver state, IVIS state and the associated cognitive operations imposed on the driver, and driver performance. Specific conclusions regarding the specific data that need to be gathered include:

- Criteria used to select candidate measures of distraction include the need for timely, diagnostic, sensitive, and practical measures.
- For physiological measures the most promising include eye movements, eye blinks, and the 0.1 Hz variability of heart rate
- For driving performance, promising measures include lane position, speed control, and headway maintenance.
- For IVIS interactions, MRT and OFM-COG offer a promising means of anticipating the demand likely to be posed by the IVIS.
- It is likely that relationships between these variables might be particularly powerful predictors of distraction, such as eye movements and steering behavior.
- The complex and non-linear nature of the data predicting distraction may be best analyzed with sophisticated algorithms, such as Hidden Markov Models (HMM) and Support Vector Machines (SVM).

These conclusions also highlight important gaps in the research base needed to estimate driver distraction and support adaptive information systems for drivers. To fill these gaps two experiments are proposed. The first addresses four critical issues:

- The degree to which IVIS interactions, physiological, and driving performance measures, alone and in combination, can predict reaction time decrements
- Investigate whether distraction affecting tactical performance displays a different signature compared to distraction affecting control performance
- Assess how individual and generic models affect the precision of the predicted distraction
- Assess the robustness, reliability, and specificity of traditional linear regression, Hidden Markov Models, and Support Vector Machines in predicting driver distraction

The second experiment complements the first and addresses the issue of strategic task management as it relates to distraction.

- Address how periods of low and high activity influence resource allocation and effort investment
- Investigate how IVIS characteristics influence attentional withdrawal and driving task preemption.
- Investigate how driver-initiated and IVIS-initiated influence drivers' decision to engage and persist with IVIS interactions.
- Assess task inertia effects on driver distraction

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