ABSTRACT

ZHANG, YU. Visual and Cognitive Distraction Effects on Driver Behavior and an Approach to Distraction State Classification. (Under the direction of Dr. David B. Kaber).

Contemporary in-vehicle devices address driver information, communication and entertainment needs, but pose additional distractions to driving. Despite the diversity of technology, there are two principal forms of driver distraction, including visual and cognitive. Understanding how distractions may change driver behavior and developing methods to detect distraction can support effective design of assistive technologies for mitigating driving safety threats.

Unfortunately, the majority of previous studies in driving distraction have focused on operational driving tasks, such as lane keeping. The simplicity of evaluated driving tasks limited the applicability of results to real-world environments. Related to this, the designs of visual and cognitive distracter tasks in previous studies failed to pose cognitive conflicts with driving tasks, or did not present a unique form of distraction in terms of driver cognitive processes. In addition to this, there has been a lag between theoretical description of driver internal processes and empirical assessment of awareness, for example.

To address the above limitations, the objective of this study was to assess driver performance and awareness effects of in-vehicle visual and cognitive distractions, which uniquely interfere in driver cognitive processes, during operational and tactical driving tasks. The study followed a (2x2x2) factorial experiment design with two levels of driving control (i.e., operational vs. tactical), the presence or absence of visual distraction, and the presence or absence of cognitive distraction. Twenty young drivers participated in the study and each

performed 8 experimental trials. Each trial presented one out of eight combinations of controlled variables, involving a primary task of lead-car following or passing under a predefined distraction condition. This study collected both driver overt performance and internal behavior measures. Overt behavior measures included eye-tracking and vehicle control performance. Internal process metrics included situation awareness and perceived workload.

Experiment results revealed driver vulnerabilities to visual and cognitive distraction depended on the concurrent driving control mode. Visual distractions led to increased off-road glances and speed variances. However, drivers showed adaptation to such distraction and maintained their situation awareness for safety, particularly in following. Cognitive distraction became challenging when tactical driving were required. Drivers showed significantly degraded situation awareness and driving performance when performing passing tasks under cognitive distraction. Furthermore, the simultaneous occurrence of both visual and cognitive distraction appeared to limit adaptive behaviors, even under an operational control mode.

Beyond contributing to understanding the effects of distraction on driver behavior, this study extended previous research on driver distraction states classification to a broader range of driving control (i.e., including tactical tasks). A support vector machine (SVM) was selected as the basis for classifying driver distraction states (visual, cognitive， and combined) for both operational and tactical driving control. The data from the experimental part of the study was used to train and test the classification algorithm. Results of the classification suggested that drivers' distraction states can be inferred through driver

behavior changes. Analysis of cognitive distraction on the basis of driving tasks promoted the efficiency of classification. In addition, the present research demonstrated the additive value of real-time measures of driver internal processes in distraction classification.

In summary, this research broadened the current knowledge of the implications of driver distraction in different driving tasks. The work revealed the potential for distraction state classification at different levels of driving control. The classification algorithm included inputs representing real-time measures of driver internal and overt behavior. The outcomes of the study reduce the gap between driver distraction theories and empirical findings, as well as provide valuable information for developing effective assistive technologies and in-vehicle distraction mitigation systems.

Visual and Cognitive Distraction Effects on Driver Behavior and an Approach to Distraction State Classification

by
Yu Zhang

A dissertation submitted to the Graduate Faulty of
North Carolina State University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Industrial Engineering

Raleigh, North Carolina

2011

APPROVED BY:

Christopher Mayhorn	David Dickey
Joseph Hummer	Russell King
David B. Kaber Committee Chair	

BIOGRAPHY

During the completion of this dissertation, Yu Zhang worked as a research assistant in the Human Factors and Ergonomics (HFE) Area of the Edward P. Fitts Industrial & Systems Engineering Department at North Carolina State University. Her research was supported in part by a grant from the National Science Foundation (Grant No. IIS-0905505) with a focus on simulation design for human performance assessment. She also received support from The Ergonomics Center of North Carolina. Prior to this, Yu Zhang received her Master's degree from the Department of Industrial Engineering at North Carolina State University in 2009, and her Bachelor's degree from the Department of Automotive Engineering at Tsinghua University in 2007. Her major research interests include human computer interaction and driver behavior modeling.

ACKNOWLEDGEMENTS

I would like to express my deep and sincere appreciation to a number of people, whose help was crucial in the completion of this dissertation.

First of all, I have been privileged to have the direction and guidance of Dr. Kaber. Without his passion in expanding the current knowledge of driving behavior, I would not have had the chance to explore this fascinating area and contribute to the development of driver assistance technology. Dr. Kaber has always been generous with his time since the beginning of this project. His consultation with me was always an inspiring and rewarding experience. With his professional advice and his faith in me, I conquered all challenges in the course of my study.

I owe a debt of gratitude to my committee members, Dr. Dickey, Dr. King, Dr. Hummer, and Dr. Mayhorn, for their time, effort and expertise in supporting me at various stages. Dr. Dickey helped me with statistical analysis; Dr. King prepared me with mathematical analysis skills; Dr. Hummer motivated me to ensure this research had practical utility; Dr. Mayhorn provided me with critical observations on the research and strengthened my writing with his deep understanding of the human factors domain. I would like to thank all of my committee members for helping me to form a rigorous and meaningful dissertation.

My heartfelt appreciation also goes to my esteemed and dear coworkers, Yulan Liang, Meghan Rogers and Wu Chen, for their whole-hearted support and invaluable assistance. Yulan made substantial efforts in initiating the study, conducting experiments and processing raw data. Meghan and Wu worked diligently in planning the study and running the experiments. Meghan also made significant contributions to the data analysis and generation

of results based on the study. I enjoyed working with them and benefited much from discussions with each of my team members.

I would also like to express my gratitude to Cecilia Chen and Dr. Fathi for their consistent assistant in my doctoral program. I am also grateful to all the technicians in the department, who were always professional in technical support. This was important to the set-up and maintenance of a well-structured experimental environment.

My gratitude also goes to the people who consented to participate in my study. Their willingness to follow the procedures made this research possible, and their suggestions were critical to the outcomes of the study.

Last but not least, I owe my deepest gratitude to my dear family. It is a great honor for me to repay their faith in me with one of the most important accomplishments in my life. To my parents, Fuxiang Diang and Lijun Zhang, thanks for supporting me with your encouragement and caring. Your unwavering commitment to your own research has been a model for my work and will serve to motivate my future career. You also made me believe in myself and that I could achieve my goals. I hope that you can be as proud of me as I am to be your daughter.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
AOI	Areas of Interest
ATC	Air Traffic Control
BN	Bayesian Networks
CV	Cross Validation
GDTA	Goal Direct Task Analysis
FIS	Fuzzy Inference Systems
HMM	Hidden Markov Models
MRT	Multiple Resource Theory
PCA	Principle Component Analyses
RBF	Radial Basis Function
SA	Situation Awareness
SART	Situation Awareness Rating Technique
SAGAT	Situation Awareness Global Assessment Technique
SME	Subject Matter Expert
SPAM	Situation-Present Assessment Method
SVM	Supportive Vector Machine

CHAPTER 1 INTRODUCTION

Advances in electronic technology have strengthened the bond between drivers and in-vehicle devices. Contemporary devices provide drivers with enhanced information, communication and entertainment services. At the same time, they represent additional distractions to drivers. In the U.S., accidents related to distraction accounts for 13~50% of all crashes and result in as many as 10,000 deaths each year (J. D. Lee, 2006). This motivates the need for new technologies to provide warnings or adapt vehicle system functions based on the driver states of distraction (Engström & Victor, 2010; Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006).

Driver distraction is defined as "a diversion of attention away from activities critical for safe driving toward a competing activity" (J. D. Lee, Regan, & K. L. Young, 2009). Two forms of distraction are commonly associated with contemporary in-vehicle devices, namely visual distraction and cognitive distraction. The former takes a driver's "eyes-off-road", while the latter takes their "minds-off-road" (Victor, 2005). To reduce safety threats posed by these two forms of distractions, human factors researchers need to solve two problems. The first is identification of how driver cognition is affected by the two types of distraction and the second is determining how to classify driver distraction states based on the types of distraction to which they are exposed.

The first question has been addressed for low-level driving control, i.e. operational tasks (Boyraz, Sathyanarayana, & Hansen, 2010; Liang, 2009). However, driving is a complex control process involving multiple-levels of control (J. D. Lee et al., 2009). Low-level driving control may be affected by driver distraction states in the same manner as other

levels of control. Related to this, naturalistic driving data have been used to investigate driver distraction effects with a particular focus on visual distraction identification (Klauer et al., 2006). One challenge of such an approach is the need for tight controls on experiment conditions. It may be difficult to eliminate nuisance variables (e.g., fatigue) in driver performance and to isolate the effects of specific types of distracters. The second problem, i.e., distraction state classification, requires a solution to the first problem as a basis for structuring the classification approach. As a result of these issues, there is a need to extend current lab-based research to cover a broader range of driving tasks and to attempt to isolate the effects of particular types of distracters on driver behavior.

As a contrast to the limitation of empirical research area, a number of theories have been developed to understand distraction mechanisms in driving, e.g., control theory, information processing models, multiple resource theory and situation awareness models (Bolstad, Cuevas, Wang-Costello, Endsley, & Angell, 2010; Horrey, Wickens, & Consalus, 2006; J. D. Lee et al., 2008). These theories elaborate cognitive processes and essential elements related to driving from various perspectives, providing the possibility to estimate the consequences of distraction. The following sections explore these theories to identify key elements of driver and environment interaction leading to interference in cognitive mechanisms according to types of distraction, and potential solutions for classifying driver distraction states.

1.1 Situation Awareness in Driving

In order to perform complex operational, tactical and strategic tasks, before selecting actions, drivers need to develop internal representations of current driving conditions based on perceived cues and task goals. The formulation of such representations is encompassed within the construct of situation awareness (SA). As defined by Endsley (1995a), SA is operator perception of elements in the environment within a volume of time and space, comprehension of their meaning relative to task goals and projection of future states. Inattention caused by distractions is evidenced by error in SA, which may lead to improper responses to environment cues (Bolstad et al., 2010).

The relationships among distraction, driver SA, and performance, can be illustrated as a three-stage cycle diagram (see Figure 1-1). First, distraction mediates accuracy in driver achievement of SA based on environment cues. Second, insufficient SA leads to poor driver decisions and behaviors. Third, changes in drivers behavior can be used to infer the existence of distractions. The following sub sections support these arguments in detail.

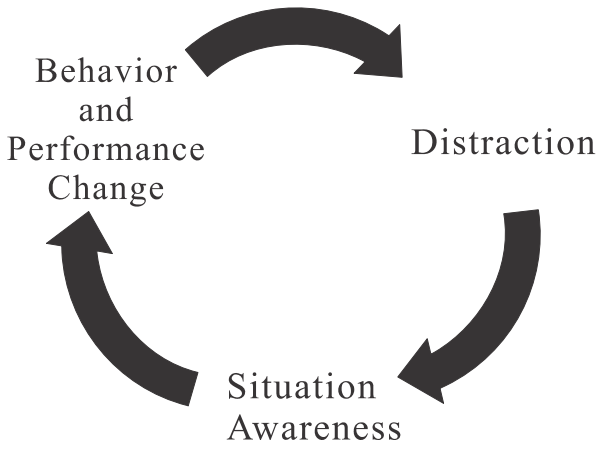


Figure 1-1. Relationship of situation awareness, distraction and driver behavior.

1.1.1 Information processing and a three-stage model of SA

The framework of SA, as proposed by Endsley (1995b), follows an information processing model scheme along with representation of the state of a dynamic environment. As shown in Figure 1-2, SA bridges environment cues and driver decisions (Matthews, Bryant, Webb, & Harbluk, 2001). According to its definition, SA can be broken-down into three levels, consisting of perception (Level 1 SA), comprehension (Level 2 SA) and projection (Level 3 SA) (Endsley, 1995a). Perception involves extracting critical information from incoming stimuli. Comprehension involves integrating obtained information to form an understanding of the current driving condition. Projection involves estimating future states of the driving environment based on current information.

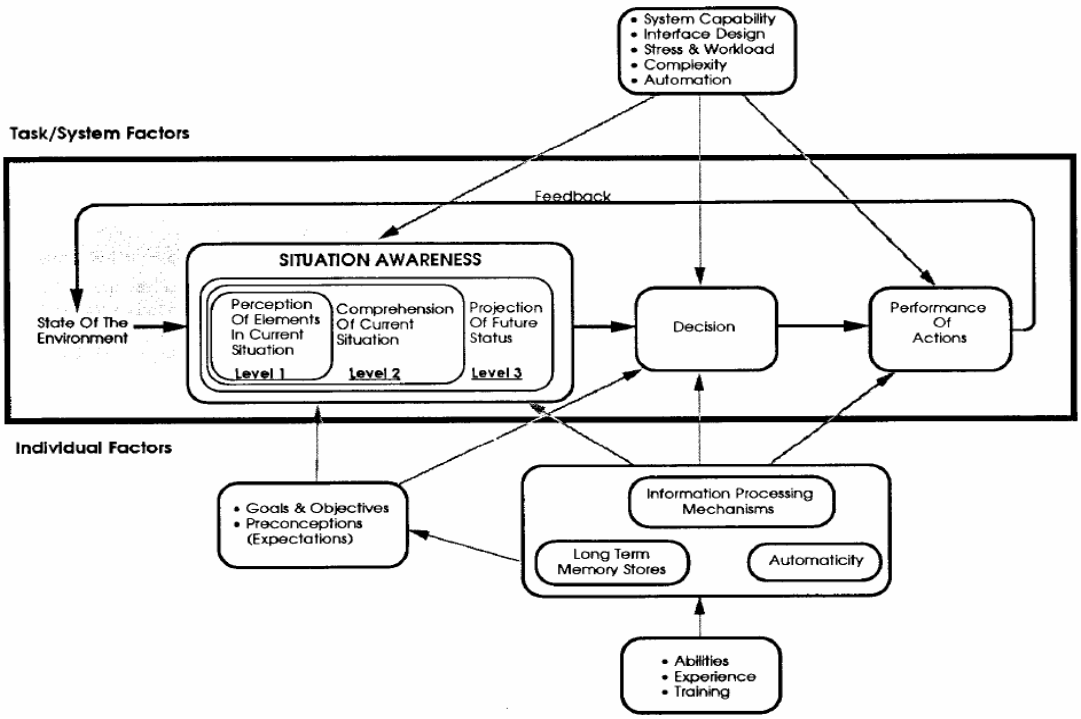


Figure 1-2. A model of situation awareness in dynamic decision making (Endsley, 1995b).

In this framework, SA is a separate construct from the sensory process, decision making and action. Achieving SA requires sensory input and use of working memory. Introducing distraction may intervene in sensory processes or compete for working memory, and may eventually degrade SA and performance (Ma & Kaber, 2005; Zhang, Jin, Garner, Mosaly, & Kaber, 2009).

The levels of SA required for performance depend on the requirements or modes of operator behavior to be supported (Wickens, J. D. Lee, Y. Liu, & Becker, 2004). According to Rasmussen (1983), there are three modes of cognitive control behavior, including automatic or skill-based processes, intuitive or rule-based processes, and analytical or knowledge-based processes. These modes of behavior are distinguished from each other by specific cognitive activities (see Figure 1-3). Automatic or skill-based processes involve selective attention to capture environment cues and automatic responses to perceptual cues. These processes pose a very limited load on cognitive resources and tend to be utilized when operators are extremely experienced with a task, for example, following road curvature. The need for SA in such processes is negligible. Rule-based processes typically occur when operators are familiar with the rules of a task but haven't developed extensive experience to make intuitive responses. Such processes primarily rely on Level 1 SA to extract critical environmental cues, which are matched with appropriate actions through predefined rule sets, for instance, conforming with traffic lights. Working memory is used to facilitate cue integration and rule-based action selection. Analytical processes rely heavily on mental simulation, which requires both Level 2 and Level 3 SA. Level 2 SA supports validation of information about the current situation, which forms the basis for further analytical

processing. Level 3 SA supports mental evaluation of action plans, the required task timeline and expected outcomes associated with plans. Beyond cue integration, working memory is used to support mental simulation and generate action plans. Therefore, analytical processes are much more cognitively demanding compared to the other two types of cognitive processes.

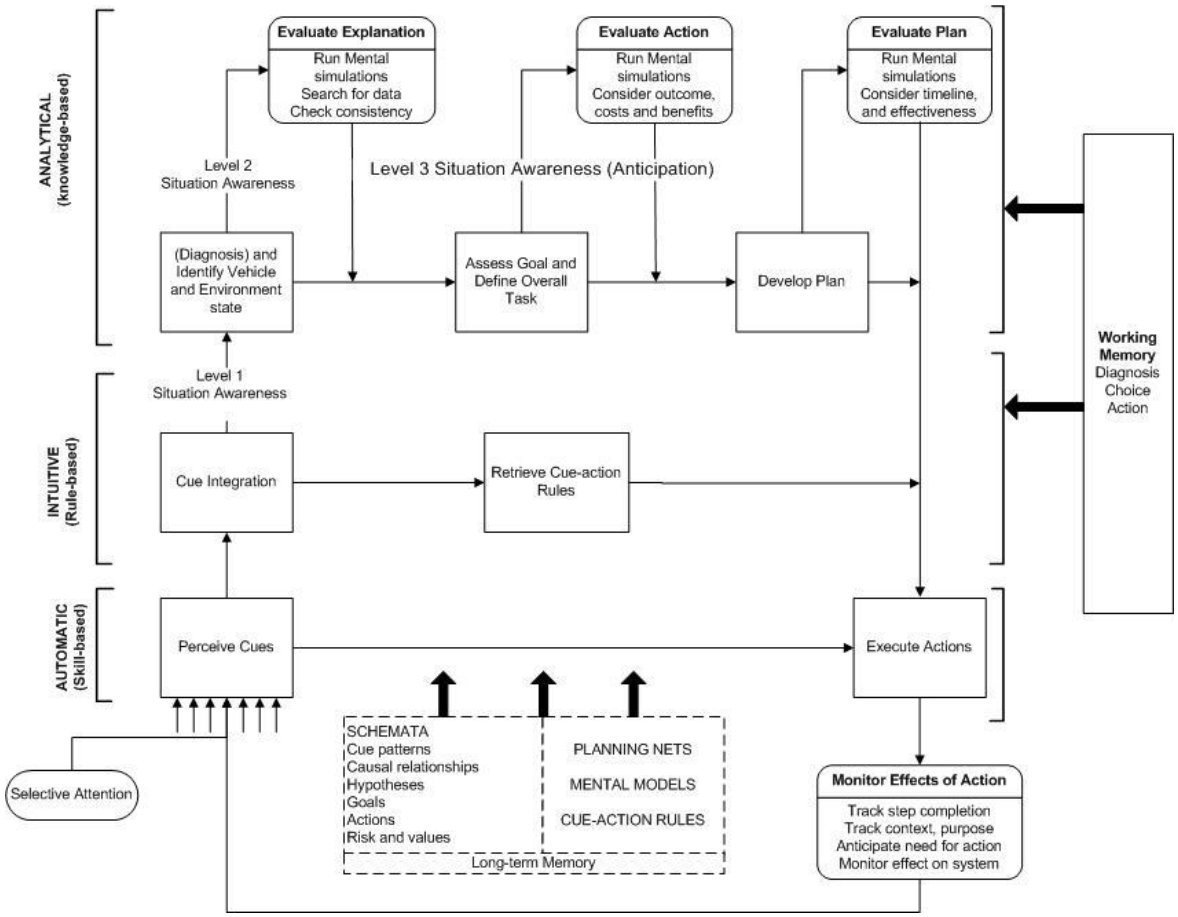


Figure 1-3. Integrated decision making model, adapted from Rasmussen (1983) byWickens, et al., (2004).

The effects of the three cognitive control modes are monitored to provide feedback to the operators and facilitate the modification or correction of operation decisions. Feedback

mechanisms complete the closed-loop of cognitive control. Perceptual cues and actions can be connected through any of the three cognitive control modes, and links posing minimal cognitive demands are preferred by operators, provided they yield satisfactory performance. Related to this, knowledge–based behavior is only exhibited when there is sufficient time for analytical processes and there is no satisfactory solution from skill- and rule-based processes.

Because driving tasks involve all three modes of cognitive control behavior, the reliance on specific cognitive mechanisms and SA can be analyzed on a control mode basis. The next section identifies connections between driving tasks and cognitive modes and discusses the SA requirements of different tasks.

1.1.2 Levels of driving control and situation awareness

Driving tasks are commonly categorized in terms of a three-level hierarchy, including strategic, tactical, and operational control (Michon, 1985). Each level of control is related to a specific set of goals. The ‘‘strategic” level corresponds to route planning under general constraints, such as a pre-defined arrival time, or optimization criteria, like shortest travel time, to satisfy global goals (i.e., arriving at a place within a certain time). The ‘‘tactical” level corresponds to developing plans to realize near-term goals (e.g. making a left turn at a intersection) based on the instantaneous driving situation. The ‘‘operational” level corresponds to implementing vehicle control actions, such as speed control and steering control, to satisfy basic driving goals (e.g. maintaining the speed limit and avoiding collisions).

Based on required skills and control, Michon's classification of driving tasks (1985) is closely connected to Rasmussen's taxonomy (1983) of cognitive behavior. Consequently, the levels of SA support can also be associated with the levels of driving control (Jin & Kaber, 2009; Ma & Kaber, 2005; Matthews et al., 2001). As illustrated in Figure 1-4, operational tasks mainly rely on skill-based behavior. At this level, only Level 1 SA may be occasionally used for monitoring purposes. When error messages occur (e.g., steering wheel resistance), they may invoke the requirement for Level 2 SA. Tactical tasks may be dependent on all three operator modes of cognitive behavior. The contribution of each mode largely depends on driver expertise. In tactical tasks, drivers mainly process near-term maneuvering goals and make short-term projections. Therefore, there is a high requirement for Level 1 and 2 SA; while there is limited reliance on Level 3 SA. Without navigation aids, strategic tasks are largely dependent on knowledge-based behavior (Bellet, Bailly, Mayenobe, & Banet, 2009; Bellet, Bailly, Mayenobe, & Georgeon, 2007). At this level, drivers make long-term projections of traffic patterns and times and require greater Level 3 SA compared to the other two types of tasks.

In summary, there are considerable differences in the SA requirements of the different driving control modes. Related to this, it is possible that the influence of distractions on SA and the consequent degradation in performance depends on the levels of control required by driving tasks.

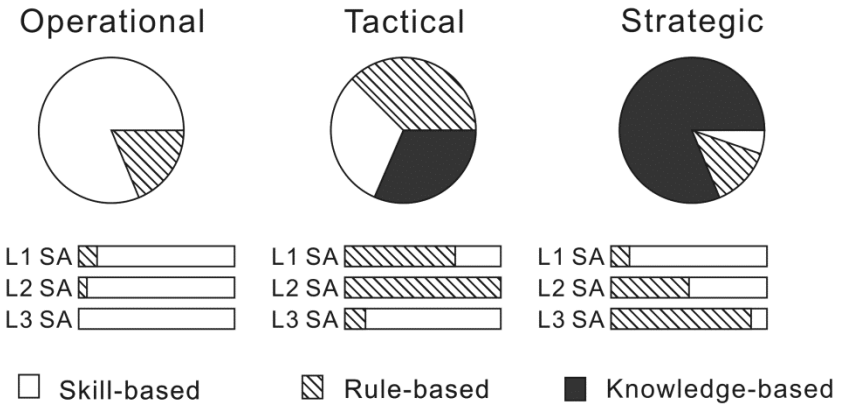


Figure 1-4. Degrees of dependence of driving behavior on levels of SA, adapted from Matthews et al., (2001).

1.1.3 Implicit vs. explicit awareness

The three-stage model of SA proposed by Endsley (1995a) suggests a sequential formulation of SA, i.e., higher-level SA depends on lower-level SA. The quality of driver SA at each level depends on SA at the preceding level and dictates the quality of driving performance. However, such a conceptualization of SA may not be sufficient for interpreting driver internal processes in dynamic driving environments. It has been shown that human operators of complex systems often make decisions under uncertainty (before accurate SA is achieved), and deficiencies in lower-level SA are not necessarily correlated with deficiencies in higher-level SA (Hoc & Amalberti, 1995). That is, drivers may still exhibit "good" performance even when they have insufficient SA. They may make "good" higher-level decisions about routes even though they have "poor" operational driving performance. Such "exceptions" make the effects of distractions on driver SA and performance difficult to

predict. Hence, to provide an additional basis for “exceptions” on driver SA, a complimentary model to Endsley’s SA representation is described below.

Bellet et al. (2009) proposed a three-dimension SA model, including implicit, explicit and reflexive awareness (see Figure 1-5). Reflexive awareness is a supervisory component to guide explicit awareness, which is related to long-term learning and high-level decision making (judgments). It encompasses two dependent aspects of meta-cognition, including ‘‘behavior conceptualization” and ‘‘judgment of values”. Behavior conceptualization refers to elicitation of operative knowledge of one’s own actions, which facilitates formation of an operational behavior frame of reference. Judgment of values refers to risk assessment and attitudes in relation to risk-taking.

When operators are habituated (accustomed) to a task set, their decisions and actions may only be based on two types of SA, either implicit or explicit awareness. Implicit awareness relates to, for example, highly automated driving behaviors, while explicit awareness refers to effortful action, intention and decision making in Bellet et al. model. The representations and knowledge stored in LTM connect with each other by two independent regulation loops which serve explicit and implicit awareness separately.

Transitions may occur among explicit and implicit awareness via two processes, namely “emergence” and “immergence”. The “emergence” process brings implicit awareness up to explicit awareness. It can occur either in the short term or long term. Short-term emergences are introduced by interruptions in explicit awareness (e.g., changes in the driving environment, conditions leading to operator selection of a new set of rules for behavior). Long-term emergences are caused by the driver’s own performance strategies (e.g. self-

evaluation while driving), transmission of one's competence to another driver (i.e. traffic negotiation), or justifying one's actions (i.e., retrospective explanation of previous actions in driving situations). As a counterpart of "emergence", the "immergence" process transitions explicit awareness down to implicit. This process is to account for decision making embedded in strong stimulus-response associations and the phenomenon of explicit thought becoming implicit knowledge with learning practice over time.

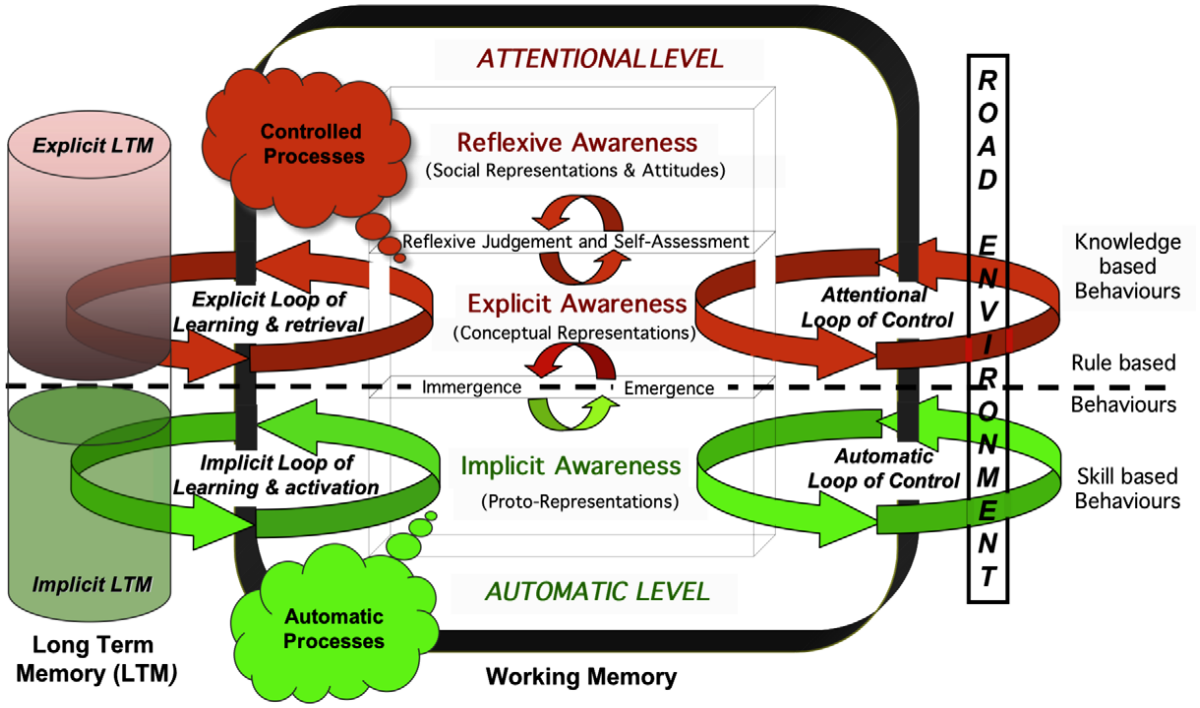


Figure 1-5. Levels of awareness and activity control loops. (Bellet, et al., 2009).

Rather than competing with the three-stage SA model from Endsley (1988), this architecture provides a different perspective on the relationship between SA and task performance, which may help to provide a more complete understanding of how perception, comprehension and projection influence operational, tactical and strategic driving behaviors. For example, according to Bellet's model, drivers may fail to perceive the brake light of a

lead vehicle or to be aware the lead vehicle is traveling below their current speed due to distractions; however, they may still exhibit good performance in passing the lead vehicle and maintaining legal speed, because such a situation represents a well-learned traffic pattern in implicit awareness and they can respond without incurring explicit awareness. However, information processing based on implicit awareness needs to address concurrent driving task performance in order for the result of the information processing to be retained. For example, drivers may perceive a roadway billboard, but if the information is not recognized in explicit awareness and used in decision making and action, the driver may not have recall. This can also be referred as an instance of inattention blindness in driving (Strayer, Drews, & Johnston, 2003).

Bellet et al.'s theory (2009) suggests that explicit and implicit awareness across all levels of driving control constantly changes according to the present driving task. The coexistence of explicit and implicit awareness follows two fundamental assumptions: 1) safety is the first priority under all circumstances; however, 2) drivers tend to minimize the use of cognitive resources. Under these two assumptions, the relationship between SA and levels of driving control can be reasonably described. Explicit awareness is more cognitively demanding, as compared to the implicit awareness; therefore, drivers will typically rely on implicit awareness and operational maneuvers to accomplish tasks. Even for tactical decisions, drivers will attempt to use implicit awareness and skill-based behavior in decision implementation. However, tactical decisions often require active monitoring of the environment to guarantee the accomplishment of defined goals. Such monitoring depends on an explicit form of situation awareness. In addition, explicit awareness may be invoked by

emergent driving tactical behaviors. Once abnormal or critical situations occur, or the limits of routine behavior are exceeded (i.e., outcomes of a certain action are not in-line with expectations), the highest level of awareness (explicit) becomes active and control is taken over by rule-based and knowledge-based processes. Although making a strategic decision (e.g., navigation, route selection) requires explicit roadway environment awareness, it is possible that drivers engage in automatic control modes and use implicit awareness when the driving environment is familiar or known to them. These explanations of how SA may be used at different levels of driving control will be used as a basis for interpreting the empirical findings of this research.

1.2 Distraction Vulnerability of Driving Tasks

In addition to fluctuations in primary driving task demands, secondary task demands and modalities of distraction may contribute to variations in driver performance and safety status (Horrey & Wickens, 2004). This subsection briefly reviews the influence of distraction modality on driver behavior, and identifies forms of distractions meriting comprehensive examination due to potential safety issues.

1.2.1 Sources of distraction and Multiple Resource Theory (MRT)

Driver distractions may occur due to in-vehicle devices. However, in order to promote the applicability of research to a broad range of driving circumstances, it is necessary to distill the underling elements of distraction from various agents and to test abstract forms of distraction representing common elements. Abstract representation of distractions can be based on two dimensions, including: 1) a physical event or an object that

presents distraction; and 2) the action performed on that event or object (Regan, K. L. Young, J. D. Lee, & Gordon, 2009). Wickens' multiple resource theory (MRT) of attention in information processing has been recognized for its capability to predict effects of distraction on perception, information encoding, and response execution. Here it is applied to reveal the principle elements of distractions and further facilitate abstract representation of distraction in driving tasks (Wickens, 1984, 2002).

MRT has a four-dimensional structure, including stages (perception and cognitive activities vs. response execution), sensory modalities (auditory vs. visual), codes (verbal vs. spatial) and channels (focal vs. ambient). If manipulation of an in-vehicle device competes for the same cognitive resources that are required by driving along any of these four dimensions, it may degrade driving performance and safety.

It is known that driving involves visual perception, spatial coding of information, and manual manipulation (Liang, 2009; Regan et al., 2009; Wickens et al., 2004). It requires focal vision to obtain critical environment cues and use of ambient vision to facilitate lower-level vehicle control, such as lane keeping (Horrey et al., 2006). Hence, a visual distraction usually refers to a task that attracts focal vision away from the driving task and that typically involves manual responses. A cognitive distraction task in driving usually refers to a task that requires spatial coding (i.e., coding processes using location and orientation as cues). These two types of distractions have different mechanisms that compromise the driving cognitive process. The prior causes perceptual modality (visual channel) and motor control stage competition with driving, while the later leads to coding (verbal or spatial) and cognitive processing stage competition (Regan et al., 2009).

Changes in driver behavior due to different distraction mechanisms have been identified in earlier simulator or in vivo studies. For example, visual distraction has been found to increase the dispersion of eye gaze pattern from the roadway (Donmez, Boyle, & Lee, 2007; Liu, 2001), while cognitive distraction has been found to reduce gaze scatter but result in insufficient monitoring for critical elements (e.g., vehicles appearing in the rear view mirror) (Recarte & Nunes, 2003; Victor, 2005). In terms of driving performance, visual distraction has been associated with large, discrete steering adjustments and increased lane deviations, while cognitive distraction has been associated with more frequent but smaller steering corrections (Engström, Johansson, & Östlund, 2005). Consequently, the two distraction types may lead to relatively opposite driver behavior changes. However, such inference may only be valid for lower-level driving control (operational behavior) for which differences and interactions between these two types of distraction have been assessed (Angell, 2010; Horrey et al., 2006; Liang, 2009). It remains unclear how drivers may be influenced by visual and/or cognitive distractions and their interactions during higher-level driving control (tactical and strategic behavior).

Beyond visual and cognitive distraction, drivers may sometimes receive haptic cues from the driving environment, such as the perception of rumble strips on the highway. MRT may also be extended to include the tactile modality in attention allocation analysis (Boles, Bursk, Phillips, & Perdelwitz, 2007). However, since the majority of current in-vehicle devices only use visual and auditory interfaces and very few, if any, cause haptic distractions, visual and cognitive distraction remain the focus of driving distraction research.

1.2.2 Adaptive safety behaviors in response to distraction

Driving is a complex combination of multiple manual control tasks with different task structures (e.g., modalities of information presentation) and levels of difficulty. As proposed by Wickens (2002), multitasking resource capacity and resource demands (i.e., task difficulty) affect time-sharing between driving and distraction tasks. Attention allocation strategies and the timing of operation execution may be adjusted to address certain levels of task difficulty (Fuller, 2005) and ensure sufficient cognitive resources are available for increased demands in one task or another (Horrey & Simons, 2007). Driver behavior adaptation to visual distractions was first described by Senders et al. (1967). They suggested that when drivers look away from the road, uncertainty about the roadway situation increases. When uncertainty reaches a certain threshold, drivers look back to the road. Wierwille (1993) quantified this threshold of off-road glance duration at 1.8 seconds on a straight road and 1.2 seconds on a curve on average for a normal driver. Such thresholds may vary as driver speed or road condition changes and may be subject to individual differences.

Driver behavior adaptations to cognitive distractions have also been observed. Under cognitive distraction drivers tend to increase headway distance to a lead vehicle when engaged in a following task, which only requires instantaneous braking and accelerating (Strayer & Drews, 2004; Strayer et al., 2003). As demonstrated by Horrey and Simons (2007), such behavior adaptation may not be applied when driving tasks involve higher-level control, such as tactical passing maneuvers. This finding, however, is in contrast with MRT (see Section 1.2.1) and SA-based descriptions of driver information processing (see Section 1.1.2 and Section1.1.3). Lower-level operational control mainly relies on skill-based or automatic

behavior, involving visual perception and manual output. Such control is largely supported by implicit awareness of the roadway and poses limited cognitive demands. Only visual distractions may compete with driver skill-based control in terms of the perceptual modality and manual execution stage. Compared to such operational control, tactical control requires more cognitive resources. The updating of relevant task information for tactical maneuvers (e.g., vehicle positions) is also subject to higher time pressure compared to information urgency faced in car following (Horrey & Simons, 2007). Consequently, the adaptation of behavior due to cognitive distraction is expected to be greater for tactical driving, such as passing. The question is why driver behavior adaptation has not been observed at the tactical level. One explanation for this lack of adaptive compensation is that, "cognitive load is more detrimental to tactical driving than to steady-state driving and that drivers lack the resources to adjust their safety margin appropriately to maintain their target level of risk" (Horrey & Simons, 2007). This interpretation suggests adaptive behavior (e.g., headway distance adjustments, etc.) may have similar properties as tactical driving that compete for cognitive resources with other tactical behaviors.

Beyond this, the driver behavior adaptation behavior may also be complicated by the presence of both cognitive and visual distractions. Some research has shown that cognitive and visual distractions may act in an additive manner (Yi-Ching Lee, J. D. Lee, & Boyle, 2007). Other studies have shown that drivers may adapt to simultaneous distractions to a greater extent than to visual distractions (Liang & J. D. Lee, 2010). Consequently driver behavior adaptation is a complex phenomenon, which increases the complexity of distraction detection; that is, when considering adaptation as an overt indicator of distraction states, the

current empirical evidence does not allow for complete interpretation of distraction effects on driver behavior and leaves uncertainties in driving risk detection. Furthermore, driver distraction mitigation strategies are difficult to apply unless such uncertainties about the influence of distraction on driving can be reduced.

The present study addresses some of the limitations of available empirical evidence on the association of driver behavior change with distraction by using SA measures. This is expected to provide a basis for a new approach to distraction risk detection. Related to this, a summary of limitations of previous research is provided in the next section.

1.2.3 Limitations of current empirical research on driver distraction

In addition to variations in the mechanisms of distractions investigated in prior research and conflicting driver performance outcomes under specific types of distraction, the degree of cognitive and visual distraction posed by actual in-vehicle devices varies substantially (Regan et al., 2009). Therefore, there is a need to examine the types of distraction independently and jointly. Unfortunately, the available empirical evidence on driver distractions as presented in abstract forms remains inadequate. There are three major gaps that need to be filled to form a comprehensive understanding of driving distractions:

1) *Insufficient resource competition introduced by cognitive distraction*. Cognitive tasks examined in previous studies have been primarily verbal in nature, for example, arithmetic calculation (Blanco, Biever, Gallagher, & Dingus, 2006; Horrey & Simons, 2007; Ma & Kaber, 2005), word counts (Engström et al., 2005) or realistic conversation (Angell, 2010; Strayer & Drews, 2004; Strayer & Johnston, 2001). However, the cognitive processes

for driving are primarily spatial in nature. MRT suggests that verbal and spatially coded information can be processed in parallel. Hence, the artificial cognitive distractions used in previous research may not achieve maximum influence of a potential on driving task performance. It's worth noting that Angel, et al. (2006) investigated distraction tasks that competed for cognitive resources with driving and required vocal responses to verbally and spatially coded information. Twenty-two in-vehicle activities introduced either visual-manual tasks or audio-verbal tasks. One of seven auditory tasks involved some spatial processing (i.e., route selection). However, the data from all seven tasks were analyzed together to assess the general effect of cognitive distraction in this research. Although this investigation provided useful guidance on distraction task design and response metrics that might be sensitive to distraction manipulation, the implications of spatial processing on driver distraction were not identified separately. In another study, Liang, et al. (2010) applied spatial coding when designing a cognitive distraction. Unfortunately, it required a manual response, which overlapped with the response required by a visual distraction task in the same study, i.e., motor control competition with the driving task existed for both distraction conditions.

2) *Limited primary task sets*. As suggested by the literature review of models of SA, demands on driver SA depend on the required level of driving task control. It is also clear that distractions may interfere with driver attainment of SA at various levels (Matthews et al., 2001). These observations lead to another important inference that the effects of distractions on SA may also depend on the required level of driving control. Unfortunately, as mentioned

above, the implications of driver distraction on SA have only been investigated under certain levels of driving control with a focus on operational behavior.

Related to this limitation is the fact that all levels of driving control are not equally influential in safety. Strategic driving deals with global strategy for route selection and navigation. “Mistakes” at this level may only reduce travel efficiency. By contrast, SA deficiencies related to operational and tactical driving, such as underestimating the distance to an adjacent vehicle, could be fatal. Consequently, driver distraction primarily impacting strategic task performance may be less detrimental to overall system safety than distraction primarily impacting tactical behavior. In addition to this difference, the three levels of driving tasks are distinguished by the time frame on which required information processing occurs (Matthews et al., 2001). Strategic level control is mainly a top-down (knowledge-driven) process, which only executes a few times during a trip. Tactical or operational control requires bottom-up (data-driven) processes that run in seconds and milliseconds, respectively. Compared to strategic control, tactical and operational driving manipulations are more reliant on short-term information from the roadway environment. Consequently, they are more vulnerable to the presence of distractions than strategic control.

Although there have been significant accomplishments in empirically evaluating operational driving under distractions (e.g., lead-vehicle following; Ma & Kaber, 2005), tactical driving control lacks investigation. Most lab research has examined simple operational maneuvers (accelerating and braking) (Ma & Kaber, 2005; Strayer et al., 2003; R. Young et al., 2005). Even in controlled highway studies, the required level of driving control has been limited to operational behavior (e.g., Blanco et al., 2006). There have been two

attempts to assess distraction effects on operational and tactical levels of control (steady-following vs. passing). Horrey and Simons (2007) focused on cognitive distraction under such conditions and Jin and Kaber (2009) used a cell phone task that posed limited visual distraction and verbal arithmetic problems to drivers. In the prior study, safety margins, including headway time and headway distance, were applied to assess tactical and operational control; while in the latter investigation, various metrics were used to assess all levels of driving control. Unfortunately, comparisons between the two levels of control in the Horrey and Simons' study (2007) were not without confounding factors. A passing task was used to assess the modes of control, which were discriminated based on headway time profiles. Drivers were instructed to pass slow vehicles. Evaluation of tactical control was based on driver performance during passing, while assessment of operational control was based on driver performance when they followed a slower moving lead vehicle before passing. However, as defined by Michon (1985), tactical and operational control are distinguished from each other according to the internal goal state, i.e., tactical control relates to generating plans for near-term objectives, while operational control relates to basic vehicle control implementation. Consequently, drivers may be engaged in tactical planning even though they are following lead vehicles. In other words, the following-stage may be part of tactical control. Secondly, a relatively stable lab simulation of driving may lead to a reduced need for comprehension and short-term projection, as compared to real driving. Consequently, this could have reduced the cognitive load in tactical driving. Given the importance of both operational and tactical driving in driving safety and the incomplete

coverage of these two levels of control, the investigation of distraction is far from satisfactory.

Jin and Kaber (2009) addressed the influence of distraction on all levels of SA under all types of driving control through a simulation study, which used a cell phone task posing cognitive distraction and limited visual distraction. The limitation with this study was that the three levels of driving control were embedded into one driving scenario. Therefore, the study could not achieve an independent mapping of distraction effects on each level of driving control.

3) *Limited investigation of internal process*. As compared with empirical evidence of driver perception impairments due to visual distraction, there is little evidence of cognitive degradations due to distraction in spatial processing. For example, Horrey and Simons (2007) noted that change in driver manual control performance does not necessarily indicate the absence of distraction. Driver eye-tracking data and performance measures can reflect overt outcomes of complex internal processes, which may or may not be related to distraction. For example, drivers may exhibit off-road glances periodically just as a personal habit. In general, a data-driven approach to identifying detrimental effects of distraction may not be sufficient to establish a causal link between driver performance and visual or cognitive process interference. Knowing internal changes in driver understanding of the driving environment may be required to conclusively identify relationships between performance and distraction and support effective mitigation strategies for distractions.

1.3 Situation Awareness Measurement Techniques

Driver SA, or internal situation representation, can be assessed via certain techniques (Durso et al., 1998; Endsley, 1995a; Jones & Endsley, 2004; Jones & Kaber, 2004). SA-based information processing models have provided a basis for developing SA measurement techniques and the possibility to identify linkages between types of distraction in the driving environment and driver performance decrements due to failures in SA. However, because SA is internal in nature, it is difficult to develop a universally applicable and sensitive metric for assessment, especially for highly dynamic activities such as driving. The following subsections provide a summary of available techniques, as the basis for choosing a suitable SA measure for studying highly dynamic driving tasks.

1.3.1 Subjective Survey and On-line SA techniques

There are two main categories of SA measures, including subjective and objective. Subjective measures are usually in the form of surveys and ratings. They are administrated after the completion of test tasks, e.g. the Situation Awareness Rating Technique (SART) (Taylor, 1990; Taylor & Selcon, 1990). Such techniques are usually considered to be non-intrusive and lower cost. However, subject memory decay issues may bias responses, because they are usually administered at the end of an event. They may also suffer from performance bias, because participants may naturally associate positive action outcomes with high SA. Besides these accuracy problems, such techniques cannot be applied in highly dynamic operating environments or simulations, such as the driving domain.

Objective measures of SA can be classified into different categories, including freeze-techniques, real-time probes, performance measures and process indices. Among these, only freeze-techniques and real-time probes directly assess operator SA. The others make inferences of changes in SA from performance or physiological states.

With freeze-techniques, the test task or operation is interrupted or frozen during performance. Operators then answer questions about their understanding of the current task situation, which is the basis for the SA evaluation. For instance, the Situation Awareness Global Assessment Technique (SAGAT) involves blanking task displays at randomly selected times during a simulation or training exercise. Operators answer task-related questions, developed based on a goal-direct task analysis (GDTA) (Jones & Kaber, 2004), considering what they have recently experienced in the simulation. To obtain an unbiased assessment of SA, operator answers are compared with the real situation based on information drawn from computer systems or answers from subject-matter experts (SMEs) to the same questions posed to test operators (Endsley, 1995a). The validity of SAGAT has been demonstrated in numerous domains, including aviation, driving, telerobotics, etc. (e.g., Endsley, 1995b; Kaber, Onal, & Endsley, 2000; Ma & Kaber, 2005). Some studies have also shown that freezing a simulation and collecting SAGAT data does not impact expert operator performance. A freeze can take up to 5 or 6 minutes without causing memory decay (Jones & Kaber, 2004). Such techniques have also been applied in driving domain for assessing the effect of distractions (Jin & Kaber, 2009; Ma & Kaber, 2005).

However, the resolution of freeze techniques remains questionable for assessing operational and tactical levels of driving control. As suggested by Endsley (1995b), no two

freezes should occur within 1 minute of each other, while tactical and operational driving task processes occur on the timescales of seconds to milliseconds. As a result, freeze techniques like SAGAT may not have enough sensitivity to capture driver SA changes introduced by various factors such as in-vehicle distraction tasks. Although significant differences in SA have been observed under distraction vs. no distraction conditions by previous studies, all of them focused on cell phone use (Jin & Kaber, 2009; Ma & Kaber, 2005). It is possible that the substantial distraction effects caused by cell-phone use are so influential that SA changes occur in relatively large magnitude. In addition to the resolution issue, SAGAT is difficult to implement in many real-time operational systems (e.g., on-road driving) due to the need to freeze the action (Jones & Endsley, 2004). These limitations may restrict cross-validation of lab simulation results with real-world road testing outcomes. Therefore, real-time probe techniques have emerged as an alternative approach that may allow for evaluation of SA in dynamic operating environments.

1.3.2 Real-time SA probes

Real-time SA probes are different from freeze techniques in that queries are presented to participants at periodic intervals during task performance without simulation freezes. Participants answer queries regarding the situation while task displays remain in full view. Measurements usually include the response accuracy and response latency to queries (Jones & Endsley, 2004).

There are two dominant real-time probe techniques, including the Situation-Present Assessment Method (SPAM) and SAGAT-based real-time probes, which will be referred as

real-time probes in this section. The SPAM approach, proposed by Durso et al. (1998), is a real-time probe technique favoring analysis of response latency. This approach assumes that participants who maintain sufficient SA will know where to access all the critical information from the task environment. In a SPAM procedure, the operator has the opportunity to indicate his/her willingness to accept a question after a warning signal. A question is then presented and the operator responds as accurately and quickly as possible. The time duration between the occurrence of a warning signal and acceptance of a question is considered as a measure of workload, while the time duration between presentation of a probe question and the operator response is considered as a measure of SA. However, response times for incorrectly answered questions are discarded in the analysis. In SPAM, the SA questions are classified at two levels. One is present-oriented (Level 1 SA); the other is future-oriented (Level 2 and Level 3 SA). Additionally, Durso (1998) suggested recording response accuracy and making comparisons with latencies.

As an example implementation of SPAM, Durso et al. (1998) used the measurement method to study air traffic controller workload and SA. They showed individual controller ability to be predictive of SA evaluations by expert judges. However, the findings revealed few correlations between controller performance and response latency to SA queries. There was a moderate correlation between the response latency to SA probes and the SME ratings of controller performance (R^2 = .53), as well as a weak correlation between SA measures of future state with a performance measure of operation competition status (R^2 = .12).

Another study using SPAM was also conducted in the air-traffic control domain. Operator SA was assessed when controllers performed monitoring and implementation

operations under two levels of perceived workload (Willems & Truitt, 1999). Results revealed response time to accept a SPAM question was a valid indicator of workload. However, validation of SPAM was also not fully supported by this study. No difference in response time for future-oriented queries was found in terms of scenario type and level of workload. Only present-oriented questions showed significant effects of the scenario manipulation. Participants took twice as long to answer questions during high-load scenarios requiring monitoring, as compared to the three other scenarios posing lower workloads. Between this and the Durso et al. (1998) investigation, these findings raise concerns about the validity of SPAM as a real-time SA measurement technique.

Jones and Endsley (2004) attempted to validate the real-time probe approach to SA measurement using an air defense simulator study. Unlike SPAM, in Jones and Endsley's (2004) study probes were delivered to a participant by a confederate operator as part of a natural conversation during task performance. That is, probes were delivered without a warning signal and without any requirement for operators to indicate readiness. In addition, instead of categorizing probes as present and future, they analyzed operator SA according to the three-stage SA model developed by Endsley (1995a). Their formulation of real-time probes followed an approach similar to development of SA queries as part of SAGAT (i.e. using GDTA). Both accuracy and response time to probes were recorded to measure changes in SA due to experiment manipulations. The SAGAT methodology was also applied in the study to serve as a basis for validation of the real-time probe technique.

Results from the Jones and Endsley (2004) study revealed two significant relationships between SA measures and operator performance. SA probes on projection of

future states of the task environment were correlated with the number of aircraft conflicts as well as the duration of conflicts. However, results on reaction time were opposite in direction to expectation. That is, a slower reaction time was related with fewer air traffic control (ATC) conflicts. Jones and Endsley (2004) gave two possible reasons for this contradictory result. One was that operators may respond to probes with urgency when they feel time pressure. Another reason was that operators may apply a different information-gathering technique according to time allowances. Beyond this, results revealed only weak correlations between the real-time probe measures of SA and SAGAT. This was attributed to a lack of replication of probes. However, Jones and Endsley (2004) observed that the real-time probes were indeed measuring SA at some level. Both overall SA accuracy and probe response time measures were also significantly different for the two test scenarios. The independence of operator SA from workload was tested using linear regression analysis on probe response accuracy and secondary task performance. There was no significant correlation and the authors inferred that SA measures and workload reflect different aspects of operator internal processes. However, a Pearson correlation coefficient did indicate real-time probe accuracy was weakly correlated with NASA–Task Load Index (TLX) scores, which is a standard tool for subjectively measuring workload (Hart & Staveland, 1988). Therefore, it is still possible that real-time probe measures of SA may reflect some aspect of operator workload.

In addition, since real-time probes require operator articulation of their SA, it is likely that responses may actually reflect the quality of an operators' explicit awareness. As familiarity with a task increases, operators may rely more on implicit awareness to support

routine operation. Therefore, the power of real-time probes for describing explicit vs. implicit SA may depend on the complexity of the task and the expertise level of operators.

Although previous validation efforts have not demonstrated sufficient power of real-time probes for revealing all experimental manipulations, there appears to be some sensitivity of the measurement technique in highly dynamic operating environments (Durso & Dattel, 2004; Jones & Endsley, 2004). In general, several researchers consider real-time probes to be the most appropriate SA technique for evaluating operator behavior in dynamic environments (Bolstad et al., 2010). Beyond this, the validation efforts for both SPAM and real-time probe measures, described above, were conducted in the aviation domain. The evaluated tasks may have different properties as compared to driving. For example, greater "negotiation" with other human operators is expected in the driving domain compared to aviation tasks. Related to this, real-time probes may be more effective in evaluation of driver SA, because drivers must constantly monitor and project other drivers' behaviors and intentions. In support of this argument, in an investigation of age-related differences in driver SA, Zhang et al. (2009) found a significant influence of driver age and types of driving hazards on real-time probe response accuracy.

1.3.3 Critical issues in applying real-time probes

Due to the lack of conclusive validation of real-time probes, special attention must be paid when applying such techniques. First of all, neither SPAM nor the real-time probe method excluded the possibility that probes may reflect changes in operator workload. Consequently, driver workload should be recorded using a validated measure, such as the

NASA-TLX, in any study with real-time probes of SA. The outcomes of the NASA-TLX should be compared with the SA measure, and the two measures should reveal different aspects of distraction influence on driving (e.g., increased workload due to cognitive distraction may not influence driver Level 2 SA). In this way, it is possible to demonstrate the uniqueness of the SA measure in evaluating distraction. Secondly, Jones and Endsley (2004) raised the issue that a lack of replication of SA probes may lead to limited sensitivity and validity of results. Therefore, they suggested each probe be repeated 6 to 8 times to overcome the insensitivity issue. Any future study needs to use a large number of replications for reliability in statistical analysis of SA probe data. Thirdly, evaluation of SA needs to occur in conjunction with performance measures. If changes in driver SA correspond with expected performance changes, this may serve as additional cross-validation of the effectiveness of real-time probes in the driving domain.

In summary, exploring changes in driver SA and the contents of dynamic knowledge in real-time may provide additional insight on driver internal cognitive processes and the mechanism by which distraction influences performance. Real-time SA probes provide the possibility to assess driver perception, comprehension, and projection during highly dynamic task performance. With additional information on how visual and cognitive distraction impact SA and levels of driving control, this may facilitate development of effective distraction mitigation strategies, such as monitoring driver distraction state, and providing aids or warning accordingly. In the following subsections, the focus of attention will be shifted to a key aspect of distraction mitigation strategies, specifically identification of driver distraction states.

1.4 Classification of Driver Distraction State

Guided by the knowledge of potential influences of distraction on driver SA and performance, it is possible to develop techniques to classify or monitor driver distraction states. The accuracy of such classification techniques directly dictates the quality of distraction mitigation technologies, such as driver alerting systems and adaptive speed and lane control. The following subsections provide a review of applied classification techniques for identifying states of driver distraction. The review provides a basis for selection of a classification methodology that is expected to be effective and efficient under various types of driving control.

1.4.1 Visual distraction

As mentioned in Section 1.2.1, visual distraction drives focal vision from the roadway. Therefore, the classification of states of visual distraction can be based on gaze pattern. Some pioneering technologies have already been developed to monitor driver visual distraction in real time by using advanced eye-tracking systems. For example, Volvo developed a visual distraction function system (Larsson & Victor, 2008). Saab developed a visual distraction alert prototype (Karlsson, 2004) and the SAVE-IT detection algorithm was developed by Donmez et al. (2007). Common eye-tracking measures that have been applied in such technologies are listed in Table 1-1 (Duchowski, 2007; Liang, 2009).

Table 1-1. Common eye-tracking metrics.

Measures	Description
Current glance/fixation duration (GD)	The duration of a single glance at the present time
Average glance duration (AVGD)	The average glance duration within a time window
Cumulated glance duration (CGD)	Total glances duration within a time window
Number of glances/fixations (NG)	Number of fixations within a time window
Gaze percentage (GP)	Percentage of accumulated glance duration for an Area of Interest (AOI) as compared to the total cumulated glance duration for all AOIs within a time window

Note: Measures are recorded based on predefined areas of interest (AOIs).

There are two general approaches to the use of eye-tracking data in classifying visual distraction. One is "direct mapping", which applies classification algorithms directly to instantaneous eye glance measures or summarized gaze metrics over a short period of time (Bolstad et al., 2010; Donmez et al., 2007; Klauer et al., 2006). The other approach is referred to as "count-down", which compares the count of certain eye behavior measures (e.g., the number of off-road glances) or the accumulated time duration of those measures within a time window to a predefined value (Fletcher, 2008; Karlsson, 2004). No matter which glance measure is applied in a classification method, AOIs need to be defined to make meaningful inferences on the obtained eye-tracking metrics. AOIs are generally chosen based on the semantics of elements within a display or an environment, shared properties of information, and temporal aspects of tasks (Hauland, 2002). In the driving domain, common AOIs include off-road, on-road and rear-view mirror regions.

All of the above technologies have demonstrated effectiveness and efficiency in visual distraction classification, although the conditions used for evaluations were limited. The main limitation associated with "count-down" strategies is that they may suffer from time delays in detecting distractions. Meanwhile instantaneous changes in glance behavior

have shown sufficient accuracy in distraction classification without incurring any time delay (Liang, 2009). Therefore, instantaneous glance measures are recommended over using "count-down" strategies. Related to this, no specific recommendations have been made on eye-tracking measures for distraction classification. Hence, the choice of metrics in visual distraction classification may depend on the eye-tracking technology available for use.

It is also worth noting that all the studies identified above adopted simple linear models to represent relations of gaze patterns with states of visual distraction regardless of the metrics used. Additional research investigating alternate sets of glance measures for predicting states of visual distraction should be conducted using a linear classification model. Fisher Linear Discriminant (FLD) statistics are a common approach to generate linear classification models, transforming multivariate observations on gaze behavior into a univariate observation by a linear function and using the derived univariate observation to identify states of driver behavior (Fisher, 1938). This method generates a linear transformation formula to calculate a single parameter for state classification. It may also yield robust performance when multivariate normality is not satisfied. However, FLD does assume equality of population covariance matrices (Sever, Lajovic, & Rajer, 2005) and this assumption must be satisfied by input data. Quadratic Discriminant Anlysis (QDA) may be an alternative to FLD, which does not require equal variances among sample populations. However, there has been evidences showing that the robustness of QDA degrades when the distributions of inputs are not normal (Lachenburch & Goldstein, 1979; Nakanishi & Sato, 1985).

1.4.2 Cognitive distraction

Unlike visual distraction, cognitive distraction interferes with high-level cognitive processes (see Section 1.1), which depend on more than a single sensor, like the eye. As a result, the classification of cognitive distraction requires integrating data from multiple sources. Some analytical methods have been developed that can be used to infer operator internal functional states based on overt behavior inputs. Available techniques include linear Discriminant Classification (Boyraz et al., 2010), Logistic Regression Analyses (LRA) (Menard, 1995), Artificial Neural Networks (ANN) (Chen, Kaber, & Dempsey, 2000, 2004; Kaber & Perry, 2007; Tango & Botta, 2009; Wilson & Russell, 2003), Hidden Markov Models (HMM) (Oliver, Garg, & Horvitz, 2004), Fuzzy Inference Systems (FIS) (Tango & Botta, 2009), Support Vector Machines (SVM) (Kutila et al., 2007; Liang, Reyes, & J. D. Lee, 2007) and Dynamic Bayesian Networks (DBNs) (Liang et al., 2007). All of these methods have shown considerable potential for classifying operator functional states in complex work systems and may be useful for driver cognitive distraction state classification based on measures of driver behavior and performance. Referring to LRA in specific, the methodology doesn't require normality or equal variance of inputs and it can accommodate both categorical inputs and parametric inputs at the same time. However, a major limitation of LRA is that it requires a relatively large sample size to ensure performance when the number of input attributes is large (Peduzzi, Concato, Kemper, Holford, & Feinstein, 1996).

Unfortunately, comparisons of classification effectiveness and efficiency among these methods in the driving domain have been limited, including only DBN vs. SVM and ANN vs. FIS (Liang, 2009; Tango & Botta, 2009). In Liang's research, a DBN approach provided

more insight on behavior outcomes caused by cognitive distraction, but the SVM method demonstrated superior classification power. In Tango and Botta's (2009) research, an ANN showed better performance compared to a FIS approach. However, in both of these studies, assessment of driving control was restricted to the operation level. Therefore, in addition to the limited types of algorithms evaluated in these studies, they do not provide information on the utility of any methods for distraction state classification at the strategic and tactical levels of driving control.

The theory of ANNs was developed heuristically based on extensive experimentation and applications (versus building on a theoretical foundation). Related to this, the approach has several limitations (Kecman, 2005; Vapnik, 2000). First, ANN classification solutions depend heavily on the initial solution. ANNs typically use an error back-propagation (EBP) algorithm for training, which is a traditional nonlinear programming solver aimed at minimizing empirical risk (usually the squared error on training samples) by adjusting network connection weights. Because the empirical risk function has multiple local minima, the EBP guarantees convergence to any of these local minimal, but not necessarily to a global optimal solution (Chen, et al., 2004; Vapnik, 2000). However, simulated annealing (SA) approaches, involving multiple initial network solutions, have been used to attempt to identify global minima with a network. It is should also be noted that the development of ANNs using such heuristic algorithms can facilitate identification of local minima using a reasonably small number of calculations (Vapnik, 2000). Other studies using ANNs to classify operator states have demonstrated good results by appropriately selecting heuristics, such as Genetic Algorithms (GAs) and SA (Chen, et al., 2000; 2004).

Second, the selection of network architectures often lacks theoretical justification and relies on heuristics. Inappropriate selection of a network architecture may lead to "over-fitting" to training data and degrade the predictability of ANNs in testing. With this in mind, some studies have used statistical methods for input variable selection in an attempt to optimize ANN classification accuracy in testing (Chen, et al., 2004). In addition, this same research has applied general equations (Masters, 1993) for constraining the ANN architecture in terms of hidden layers and network nodes also to address potential overfitting problems.

SVMs are considered to address some of the disadvantages of ANNs (Kecman, 2005; Vapnik, 2000). SVMs emerged from theory before being applied to empirical data. Therefore, the theoretical foundations of SVM are more concrete than those of ANNs. Instead of minimizing training errors, SVMs search for global optimization solutions and minimize the number of errors on a given test set by using quadratic programming (QP). Compared to ANNs, SVMs are less susceptible to over-fitting. The results of SVMs also show less dependency on the selected kernel or architecture, as compared to ANNs (Arora et al., 2010). Related to this, SVMs demonstrate better classification capability with test data than ANNs for most popular benchmark problems (Cherkassky, 2007) and in pattern recognition practice (Arora et al., 2010). In addition, there has been a preference for the use of SVMs by predominant transportation authorities as a basis for analyzing driver cognitive states. SVMs have been recognized by both the European Commission and the Research and Innovative Technology Administration (RITA) in two essential projects, including the adaptive integrated driver–vehicle interface (AIDE) project (Kutila et al., 2007) and the SAfety

VEhicles using adaptive Interface Technology (SAVE-IT) project (J. D. Lee, Reyes, Liang, & Yi-Ching Lee, 2007).

Machine learning techniques, such as ANNs and SVMs, solve problems by exploring combinations of all available data, which may not provide sufficient insight on the relationship between data and the features that need to be identified. It has been demonstrated that irrelevant data may be weighted more in a machine learning process compared to relevant data (Statnikov, Hardin, & Aliferis, 2006). Therefore, reliance on specific data in state identification may lead to a solution for a particular set of inputs, but compromise identification of causal relations in other similar problems using slightly different inputs. In this regard, such techniques need to be applied with caution. Application of machine learning techniques in human factors research usually requires identifying behavior outcomes or predicting psychophysical indexes, which can be affected by the set of investigated state changes, prior to performing the algorithm training process (Chen et al., 2000). Some machine learning techniques, such as Dynamic Bayesian Networks (DBN), have also been applied in human operator state classification to address causality concerns (Liang, 2009). However, SVMs have shown superior classification accuracies and stability compared to DBNs (90% $\pm$ 5% vs. 88% $\pm$ 16%). Therefore, SVMs may be a superior method to ANNs and DBNs for classification of cognitive distraction states in the driving domain. The details of SVM implementation are provided in Section 1.5.

1.4.3 Simultaneous distraction

Referring back to Section 1.2.2, the behavioral consequences of previous studies have indicated that visual distraction and cognitive distraction may counterbalance each other. For instance, the concentration of gaze pattern due to cognitive distraction may offset increased gaze dispersion caused by visual distraction. Such interaction between the two types of distraction was observed in operational driving performance (Liang & J. D. Lee, 2010). If an interaction does, in fact, occur between visual and cognitive distractions, this poses a major challenge to driver state classification algorithms developed to detect a single modality distraction.

Based on this observation, Liang (2009) proposed a two-step sequential approach for separately detecting the two distraction modalities, employing two algorithms. In this approach, visual distraction was classified first, followed by classification of cognitive distraction states. The approach was developed based on two underlying assumptions. First, visual distraction is more detrimental to driver performance than cognitive distraction. Therefore, if a visual distraction is detected, driver behavior will be affected regardless of whether there is a cognitive distraction. This assumption can be easily justified by the fact that perception is a vital component in driver cognition. It is the foundation for all high-level cognitive processes in driving. Second, the presence of cognitive distraction has an influence on driver behavior independent of visual distractions. Thus, the occurrence of a cognitive distraction is not expected to affect the detection of visual distraction. Although Liang (2009) did not make the second assumption explicit in her dissertation, the classification strategy would have been inconsistent if this assumption was not met. This assumption, however, is

not supported by empirical evidence from prior study (Liang & J. D. Lee, 2010). For example, if cognitive distraction can cancel-out performance changes caused by visual distraction, the algorithm mentioned above may not detect visual distraction in the first place, when both distractions are present.

It is also worth noting that when simultaneous distractions are presented to drivers, they still show performance degradations similar to, but less significant than, what they show when posed with visual distraction only. One may argue that Liang's (2009) approach may still be applicable on this basis, because the simultaneous distraction situation may be detected as part of visual distraction. However, this argument is based on Liang's observation of operational driving and needs further examination, especially for high-level driving control. As revealed by Horrey and Simons (2007), cognitive distraction may only be influential in driver behavior during tactical driving. It is possible that rather than counterbalancing each other, visual and cognitive distraction may act additively in tactical driving and lead to greater degradation in driving performance than any of the two types of distraction. Beyond this, there is evidence showing that dual distraction conditions increased the likelihood of drivers missing safety-critical events when they drove operationally in a simulated driving environment (Yi-Ching Lee, J. D. Lee, et al., 2007). This finding is contradictory to Liang's observation (2009) and challenges the classification algorithm described above. In fact, the overall accuracy of the sequential approach proposed by Liang was low (overall: 75%) and could only identify 77% of visual distraction situations.

To avoid potential misclassification of the simultaneous distraction condition, a new classification strategy was proposed based on structured empirical observations of driver

behavior at different levels of driving control. There are three potential outcomes of simultaneous distraction conditions. First, when both visual and cognitive distraction are presented, drivers may show similar performance changes to, but less significant than, when only one distraction modality presented. In this case, the distraction modality, which determines the overall trend of behavior, should be identified first. The remaining data set should be tested to identify the presence of the other distraction modality. Second, driver performance under the dual distraction condition could be similar to no distraction conditions. In this case, a distraction classification procedure should start from either of the two distraction modalities. Any unclassified observations would be used to identify the existence of the other distraction modality. Third, the simultaneous distraction condition could be the most detrimental condition, leading to the most significant behavior changes. In this case, the dual distraction condition should be identified first, followed by classification of the other two distraction states.

Although similar overt behavior may be observed when drivers perform under different distraction conditions, driver internal processes will change according to the theoretical research in driving distraction and existing empirical evidence. Therefore, in addition to developing a new classification strategy, internal process metrics, such as SA and workload measures, should also be incorporated in the classification procedure to achieve robust and efficient identification of driver distraction states.

1.5 Implementation of Supportive Vector Machines

1.5.1 Brief introduction of SVM

Similar to many other machine learning methods, SVM does not require any knowledge of the underlying probability functions of inputs. Therefore, it is suitable to apply to high-dimensional data with non-Gaussian distributions (Kecman, 2005). SVMs map an input vector x into a high-dimensional feature space Z through an implicit mapping function Φ. The mapping function is defined by a kernel function $\kappa(\mathbf{x}, \mathbf{x}')$. The kernel function returns the inner product of mapping functions $< \Phi(\mathbf{x}), \Phi(\mathbf{x}') >$ based on two data points x and x'. In a classification process, data belonging to different classes are separated by a hyper-plane defined by Eq. (1.1), which corresponds to a decision function (Eq. (1.2)). The optimal hyper-plane is expected to minimize training errors and reveal the maximal margin of separation between two classes (Karatzoglou, Meyer, & Hornik, 2006; Vapnik, 2000). A simple illustration of the scale of a soft margin is given in Figure 1-6.

$$\langle \mathbf{w}, \Phi(\mathbf{x}) \rangle + b = 0 \tag{1.1}$$

$$f(x) = sign(\langle \mathbf{w}, \Phi(\mathbf{x}) \rangle + b) \tag{1.2}$$

where, $\mathbf{w}$ is the weight matrix defining the importance of each training data in model fitting.

Optimizing such a hyper-plane requires a solution of the following optimization problem (Cortes & Vapnik, 1995):

$$\begin{gathered} \min_{\mathbf{w},b,\xi} \left(\tfrac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{l}\xi_i \right) \\ \text{Subject to} \quad y_i(\mathbf{w}^T\Phi(\mathbf{x}_i) + b) \geq 1 - \xi_i, \quad (\xi_i > 0, i = 1, \ldots, l) \end{gathered} \tag{1.3}$$

where C is a constant, defining the penalty coefficient of an error term.; in a binary case as shown in Figure 1-6, $y_i = 1$ if $\mathbf{x}_i$ belongs to Class 1, $y_i = -1$ if $\mathbf{x}_i$ belongs to Class 2; and ξ_i is a very small positive value.

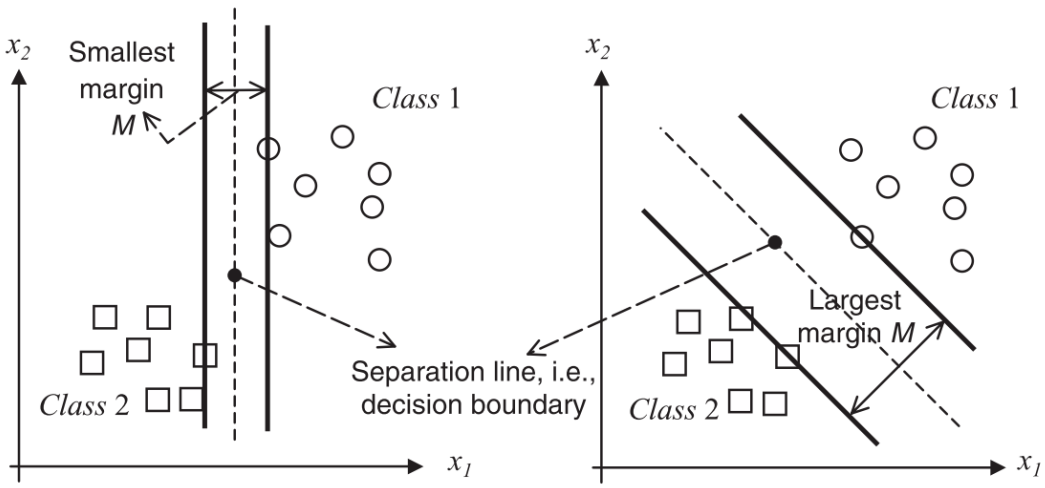


Figure 1-6. Two-out-of-many separating lines: a good one with a large margin (right) and a less acceptable separating line with a small margin (left) [reprinted from Kecman, 2005]

In a typical classification task, each instance of data contains one "target value" (y_i; i.e., a class label) and several "attributes" ($\mathbf{x}_i$; i.e., the observed variables related to the class label). Applying machine learning methods, such as SVM, in classification tasks usually involves separating data into training and testing sets. Machine learning methods produce a model to describe the relation between the "attributes" and the "target label" based on the training set; then, predications are made of class labels for the test data set. The performance of machine learning methods is commonly measured in terms of the prediction accuracy of test sets. Beyond separating data into training and testing sets, proper procedures have to be followed when constructing SVM models, which are highlighted in the next four subsections.

1.5.2 Data scaling

The attribute sets included in a classification problem may sometimes have different scales. As a consequence, scaling of inputs is recommended for machine learning processes to avoid attributes in greater numeric ranges dominating those in smaller numeric ranges. In this way, the variability of attributes may reflect their importance (Hsu, Chang, & Lin, 2003; Sarle, 2002). Theoretically, any scaling that sets to zero the mean or median or other measure of central tendency is likely to be an accurate and robust estimator of the location of the separation hyper-plane. However, due to an advantage in computational convenience and satisfactory performance, linearly scaling all attributes [-1, 1] is generally suggested (Hsu et al., 2003; Iglewicz, 1983; Sarle, 2002). It worth noting that although SVMs are a distribution free learning method, extreme outliers may degrade the efficiency of scaling (Kecman, 2005). Therefore, data screening against extreme values is still needed prior to SVM modeling.

1.5.3 Selecting a kernel function

As mentioned in section 1.5.1, kernel functions return the inner product between two points in a high-dimensional feature space. Selecting a proper kernel function is essential for SVMs. There are four basic kernels that are commonly implemented in available SVM software, including linear, polynomial, radial basis function (RBF), and sigmoid kernels (see Eq.(1.4), (1.5), (1.6), and (1.7)). Beyond these basic kernels, SVMs may be used in conjunction with neural networks. A neural network can be used to determine the number of support vectors and the SVM can be used to determine the weights (Vapnik, 2000). Many

other types of kernels have also been proposed in statistics literature, such as a Bessel function kernel or a Laplace RBF kernel.

Linear: $$\kappa(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T \mathbf{x}_j \tag{1.4}$$

Polynomial: $$\kappa(\mathbf{x}_i, \mathbf{x}_j) = (\gamma \mathbf{x}_i^T \mathbf{x}_j + \gamma)^d, \ \gamma > 0 \tag{1.5}$$

Radial basis function (RBF): $$\kappa(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma \left\| \mathbf{x}_i - \mathbf{x}_j \right\|^2), \ \gamma > 0 \tag{1.6}$$

Sigmoid: $$\kappa(\mathbf{x}_i, \mathbf{x}_j) = \tan(\gamma \mathbf{x}_i^T \mathbf{x}_j + \gamma), \ \gamma > 0 \tag{1.7}$$

In the kernel functions above, γ, r and d are kernel parameters.

Among various kernel functions, the RBF kernel is the most widely used and usually generates reasonable classification (Hsu et al., 2003; Hui & Sun, 2006; Min & Young-Chan Lee, 2005). This may be due to RBF kernels producing satisfactory classification accuracy and requiring a relatively less complicated model selection process than other kernels. The RBF kernel has only one hyper-parameter γ beyond defining the penalty coefficient C required by SVM methodology. Consequently, RBF kernels also required less complicated numeric computation than most other kernels. Although a simple linear kernel does not contain any hyper-parameters, its classification performance is usually not comparable to RBF performance, unless an input set consists of a large number of attributes (Hsu et al., 2003).

1.5.4 Estimating tuning parameters

As mentioned above, the parameters of the RBF kernel, C and γ, need to be selected for achieving a high accuracy in classifying unknown data when constructing SVM models.

The most typical tuning procedure is called “grid search”. Various pairs of C and γ are used to fit the model and identify the pair that generates the best accuracy (as illustrated in Figure 1-7). It has been found that exponentially growing sequences of C and γ are efficient for identifying tuning parameters (e.g., $C = 2^{-5}, \quad 2^{-3} \ldots, 2 -^{15}, \ \gamma = 2^{-15}, 2^{-13} \ldots, 2^{3}$).

To facilitate the tuning process mentioned above, it is essential to obtain a valid estimation of prediction accuracy or error rate of the SVM for “unknown data” (i.e., data in the test set). The k-fold cross-validation (CV) is the most prevalent approach to estimate prediction accuracy. It requires less computational effort and produces equivalent or superior performance to other estimation techniques when the sample size is greater than 150 (Japkowicz & Shah, 2011a; Weiss & Kulikowski, 1991). In a k-fold cross-validation, the training set is be divided into k mutually exclusive subsets of equal size. Data from k-1 subsets are used to train a SVM model and tested on the remaining 1 subset. Through k repetitions, all data in the training set will be predicted as “test” data at least once. This process then returns k estimates from the k repetitions. The cross-validation accuracy is then calculated as the average of the k estimates (Japkowicz & Shah, 2011a). Such a process utilizes all data collected to estimate model performance while maintaining the training data set distribution as close as possible to the “true” distribution.

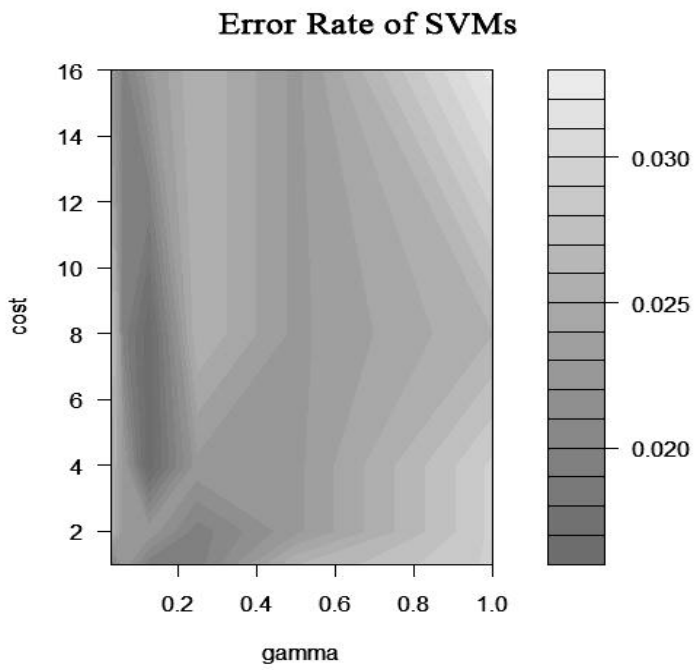


Figure 1-7. Illustration of "grid search" on $\gamma = 2^{-5},\ 2^{-4},\ 2^{-3}, 2^{-2}, 2^{-1},$, and $C = 1,\ 2,\ 2^2,\ 2^3,\ 2^4$.

The choice of k depends on the sample size and variability of the data set, and needs to balance bias and variance during model fitting (Hastie, Tibshirani, & Friedman, 2009). Bias refers to the difference between the “true” value and the estimated value based on the model. Variance refers to the standard deviation of mean accuracy estimation. With a larger k, a greater portion of data will be used for training, but fewer data will be used for testing. Therefore, a larger k is usually associated with a smaller bias in training, but a larger variance in estimation of test data. A smaller k is associated with a larger bias in training but a smaller variance in test estimation. It has been suggested that k values of 5 or 10 can produce reasonably high prediction accuracies. For problems with a relatively large instance-size, k=10 has shown better performance in classification accuracy than k =5 (Kohavi, 1995). In

addition, k=10 has been applied in similar classification problems in driver distraction (Liang, 2009; Thomas, Guan, Lau, Vinod, & Ang, 2009).

With k-fold CV as the tool for predicting estimation accuracy, the SVM parameter tuning procedure should only be conducted using the training data set. If not, a positive bias may be selected in favor of classifiers that yield the best performance with the test data set. Consequently, a separate k-fold CV is recommended with k-1 training folds to facilitate the "grid-search" process in selecting unbiased tuning parameters. Theoretically, a separate k-fold CV tuning process is referred as a nested k-fold cross validation (Japkowicz & Shah, 2011a).

1.5.5 Estimation of error rates

Although k=10 is a preferable choice in solving classification problems, this number of repetitions in training may lead to a lack of replicability of estimation results due to a small number of test data. Consequently, repeated cross validation is recommended when applying machine learning techniques in classification to achieve stable estimates of error rate. That is, classification accuracies and variances in error rates are aggregated over multiple runs as the basis for a final error rate estimation. Previous studies indicated that ten repetitions of 10-fold cross validation (i.e., 10 × 10-fold CV) usually produce high replicability of the classification results (Bouckaert & Frank, 2004; Japkowicz & Shah, 2011a; Thomas et al., 2009).

CHAPTER 2 PROBLEM STATEMENT

2.1 Research Objectives and Strategies

As stated in Section 1.2.3, previous studies of driving distraction have three major limitations: 1) the design of cognitive distraction tasks may not pose sufficient competition with driving tasks to maximize cognitive interference; 2) the driving tasks evaluated have been mainly restricted to operational behaviors; and 3) inferences on driver behavior have been made based on performance outcomes, lacking diagnostic ability with respect to internal driver processes. Furthermore, distraction classification methods have not been validated for a broad range of driving tasks including operational, tactical, and strategic behaviors. The present work addressed these limitations through a multi-stage approach, including developing additional information on driver internal processes as a basis for supporting effective design of distraction mitigation technologies. The research steps are detailed below:

First, a simulator experiment was conducted to investigate the influence of visual and cognitive distractions on driver SA in tactical and operational tasks. A real-time SA probe measure was used for this purpose (more information later). At the same time, driving performance, eye gaze and workload data were collected. In preparation for this step, two driving tasks were selected to represent the two levels of driving control. The action sets for both control levels were comparable in terms of visual and motor behaviors and time duration. Two distractions were also designed according to MRT: 1) the visual task was designed to only affect visual perception and drivers were required to make manual

responses; and 2) the cognitive distraction task was designed to only influence the spatial coding process and drivers were required to make verbal responses. This task only used auditory cues, which were inherent in the cognitive distraction.

The second step was to examine changes in SA during operational and tactical driving under different distraction conditions. Changes in SA were compared with the hypotheses derived from the SA-based information processing models. The research sought to validate the hypothesized influence of the experiment manipulation of distraction and level of driving control on driver SA. Such analysis was carried out for each level of SA in Endsley's model. Performance data, eye-tracking measures, and NASA-TLX ratings were also compared for different experiment settings. These metrics were correlated with SA measures and used to explore the relationship between SA and driver behavior outcomes. Furthermore, the performance metrics that were sensitive to the distraction manipulation were used in the next step of the research, i.e., classification of driver distraction states.

The third step was to apply a classification algorithm to classify driver states of distraction according to different levels of driving control. In this step, both overt performance (e.g., steering entropy) and internal process metrics (e.g., cognitive workload as indicated by NASA-TLX ratings and SA probes) were utilized for classification purposes.

Through these three steps, the present research attempted to: provide a structured understanding of distraction modalities in driving; assess the influence of distractions in driving behavior, especially situation awareness; and contribute to validation of classification

algorithms for accurate identification of driver distraction states. All of these outcomes provide a firmer basis for the development of in-vehicle distraction mitigation technologies.

2.2 Hypotheses on driver SA and performance

Following the literature review on SA-based information processing models (Section 1.1) and MRT (Section 1.2), this section presents hypotheses on driver perception, comprehension and projection as well as performance under visual or cognitive distractions. To facilitate presentation of these hypotheses, an illustration of the mechanisms of driver distraction is presented in Figure 2-1.

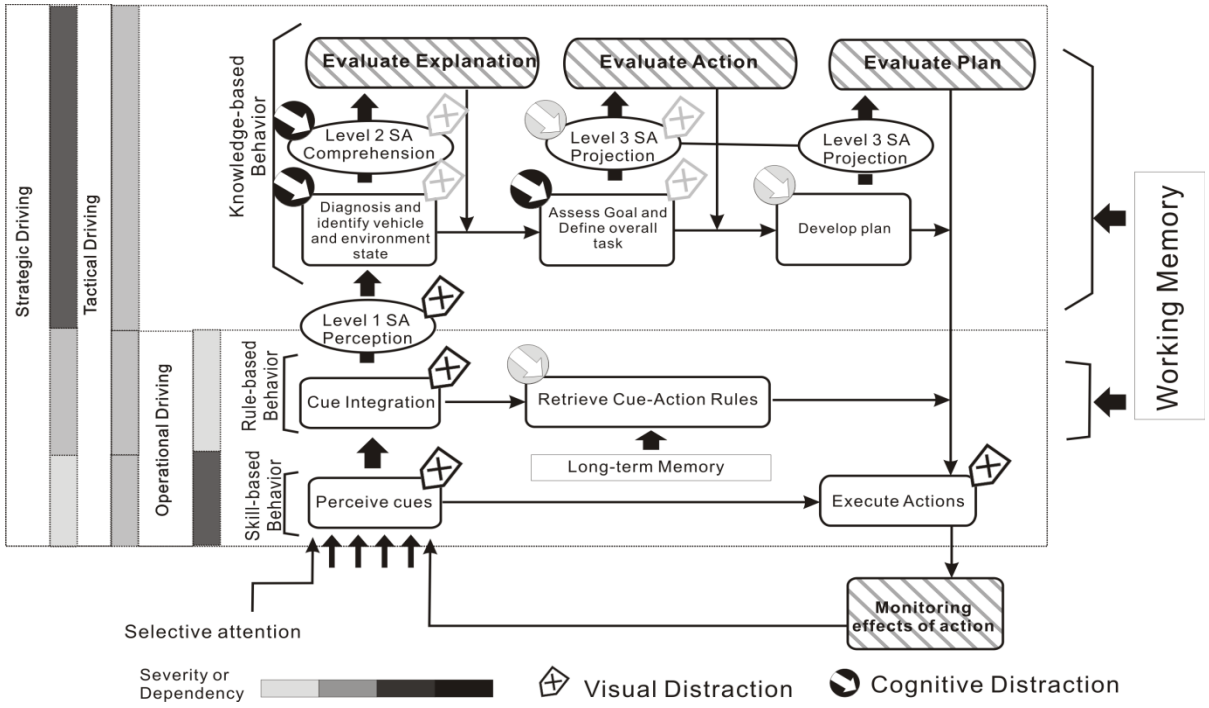


Figure 2-1. The potential influence of visual and cognitive distractions on driver SA and performance. This diagram is adapted from Wickens et al. (2004) and Rasmussen (1983)

Visual distractions are expected to attract focal vision and influence visual perception. Increased off-road glances and longer off-road glance durations may be observed during driver visual distraction. This may lead to incomplete or incorrect perception of roadway cues, which directly support the formulation of Level 1 SA (see lower left corner of Figure 2-1). The degraded Level 1 SA may lead to a corresponding degradation in Level 2 and Level 3 SA, critical to tactical (and strategic) driving control. However, the degradation of higher-level SA caused by insufficient Level 1 SA also depends on the degree of driver familiarity with the roadway environment. If drivers are knowledgeable of the task environment, Level 2 and Level 3 SA may be accurately achieved with limited cognitive effort. Consequently, even with incomplete Level 1 SA, the magnitude of degradation in higher-level driver SA may not be significant. That said, the degradation in Level 1 SA caused by visual distraction may directly and negatively affect driving performance at the tactical and operational levels due to dependence of actions on roadway perception. The influence of visual distraction on both levels of control may be similar. Specifically, the stability and smoothness of steering and speed control was expected to decrease and driver readiness to react at a specific level of control was also expected to be worse. However, as the visual distraction was designed to minimize cognitive load, any change in spatial information processing was expected to be negligible with such distraction. Consequently, drivers may have spare cognitive resources to apply adaptive strategies, such as adopting large headway distances to maintain SA and ensure safety under visual distraction.

Cognitive distraction was expected to primarily compete for cognitive (spatial) processing resources, including retrieving task rules from long-term memory and running

mental simulations in working memory (see Figure 2-1). Consequently, increased perception of workload and degraded Level 2 and Level 3 SA were expected under cognitive distractions. Driver active search for important cues in the roadway environment is based on high level cognitive activity (e.g., validation of roadway state projections) and was expected to degrade due to cognitive distraction. This hypothesis was based on prior research observing that more concentrated driver gaze patterns occur with cognitive distractions. Similarly, it was expected that active manual control of vehicle position in the roadway would be degraded, e.g., reduced steering and speed control frequency, due to cognitive loading. Since drivers may maintain focal vision on the road under cognitive distraction and perceive critical roadway elements, it was expected that they will maintain reasonably high Level 1 SA.

Operational driving control mainly involves skill-based behaviors, supplemented with rule-based behaviors when critical states develop in the roadway. From a cognitive perspective, operational control is expected to have limited dependence on Level 1 SA and even more limited reliance on Level 2 and Level 3 SA. Along with this minimal SA requirement, operational driving requires very limited cognitive resources (attention). As a consequence, operational driving may be less influenced by cognitive distraction as compared to tactical driving and yield lower driver perceptions of cognitive workload. With substantial cognitive resources, it was expected that drivers would be more likely to exhibit adaptive safety behavior (e.g., large headway distances) when making operational maneuvers than when performing tactical tasks. Such behaviors may in turn contribute to drivers

maintaining SA. In other words, there may be no significant changes in SA when drivers are only engaged in operational control behaviors.

Different from operational driving, tactical driving has been found to be highly dependent on all three levels of SA (Jin & Kaber, 2009). Therefore, it was expected to be more susceptible to cognitive distractions than operational driving. Level 2 and Level 3 SA, which rely on mental simulation and use of spatial codes, were expected to be greatly degraded by cognitive distractions along with tactical control. However, Level 1 SA may remain high due to a limited dependence on high-level cognitive processes (e.g., use of long term memory; see lower part of Figure 2-1). It was also expected that there would be fewer observations of adaptive behavior during tactical driving due to cognitive load, as well as more failures in SA due to a lack adaption, as compared to operational driving. It was expected that drivers would be less active in steering and speed control, leading to less micro-scale corrections (e.g., reduced steering entropy) but larger deviations from desired performance (e.g., increased deviation from posted speed limits).

Simultaneous distraction was expected to produce the highest workload. Failure to exhibit adaptive safety behavior was also expected to be more severe. Due to a lack of perception of critical cues in the environment, performance implications were expected to be similar to those expected for the visual distraction only condition. Decrements at all levels of SA were expected, especially for tactical driving control.

Table 2-1 presents a summary of the hypotheses on SA, workload, driving performance and adaptive safety behavior under the three types of distraction, including

visual, cognitive and simultaneous. The level of "safety threat" identified in the table reveals the degree of driver behavior adaptation. It was expected that the greater the likelihood of adaptation, the lower level of safety threat.

Table 2-1. Summary of hypotheses of the influence of distractions on operational and tactical driving

	Operational driving control			Tactical driving control		
	Visual	Cognitive	Both	Visual	Cognitive	Both
Level 1 SA	Degradation*	N/A	Degradation*	Degradation*	Degradation*	Degradation*
Level 2 SA	N/A	N/A	N/A	N/A	Degradation	Degradation
Level 3 SA	N/A	N/A	N/A	N/A	Degradation	Degradation
Off-road glances	Increased	Decreased	Increased	Increased	Decreased	Increased
Glance duration	Increased	Increased	Increased	Increased	Increased	Increased
Workload	Increased	Increased	Increased	Increased	Increased	Increased
Performance	Degradation	N/A	Degradation	Degradation	Degradation	Degradation
Safety threats	Moderate*	Low	Moderate*	Moderate	Moderate	High

Note: * means if drivers adopted adaption strategies, the degradation in performance may not occur, or the levels of safety threats may not apply; N/A means that the behavior consequences of the presence of distraction cannot be projected based on the literature review.

In general, it was expected that visual and cognitive distractions would have specific influences on driver perception, comprehension and projection for formulation of internal models of roadway dynamics. The SA processes and driver mental models were expected to significantly affect more complex tactical driving control as compared to operational control. Consequently, driver capability to exhibit adaptive safety behavior during tactical control under distraction and degraded SA was expected to be substantially worse than under operational control. In this research, headway distance was considered to be the primary indicator of adaptive behavior (Horrey & Simons, 2007).

CHAPTER 3 EXPERIMENT

3.1 Experiment Description

To investigate the influence of visual and cognitive distractions on driver behavior, a simulation study was conducted. This was the first step in this research and is detailed in the following sections. This step provided a basis for the later classification of driver distraction states.

3.1.1 Apparatus

The experiment used a high-fidelity STISIM Drive™ M400 driving simulator (Systems Technology Inc. Hawthorne, CA). Driving scenes were presented on three 38-inch HDTV monitors. The monitors were synchronized in display of visual information to provide participants a 135-degree field of view of the virtual roadway. A 5.1 surround sound speaker system was used to generate auditory feedback. Drivers interacted with the simulator through a modular steering unit with a full-size wheel, and a modular accelerator and brake pedal unit. The simulator recorded driver control actions and simulated vehicle states to log files with a sampling frequency of 30 Hz, including steering input, vehicle position, etc. Similar simulation technologies have shown validity relative to real-world driving performance and sensitivity in driving distraction-related research (Wang et al., 2010; de Winter et al., 2009).

A 12-inch HP tablet computer was placed in front of the main simulator screens. The tablet was used to present the visual distraction tasks to drivers. The screen was positioned approximately 15 degrees down and 30 degree right of the natural line of sight of participants in viewing the driving scene. A Dell desktop workstation was integrated with a sound system

to present the cognitive distraction tasks. Verbal messages were played for drivers through hi-fi speakers.

An ASL EYE-TRAC®6 Series head-mounted eye tracker with a head motion tracker (Flock of Birds 6-DOF sensor) was used to record driver eye movements at a frequency of 60 Hz. The raw eye movement data included the coordinates of the intersection of participant gaze vectors across the three screens of the simulator and the tablet PC display of the visual distraction task. Figure 3-1 presents an image of the complete driving simulator set up including a research team member wearing an eye tracker head-mount.

Figure 3-1. The STISIM driving simulator, ASL eye-tracking system (on the driver's head), and visual distraction task interface.

3.1.2 Participants

Two pilot tests, following the same procedure as planned for the formal experiments, were conducted prior to the full experiment. The purpose of these tests was to estimate the

mean and variance in driver performance under the various distraction conditions. This information was used to determine the necessary number of participants for the full experiment to achieve sufficient test power for revealing the influence of the fixed experiment manipulations on each response measure. That is to say, there was at least one response measure demonstrating a test power (1-β) greater than 0.80 for all of the fixed experiment factors.

The sample size determination was conducted with JMP 9.0 (SAS Institute Inc.). For each response measure, the effect size (δ) of one factor was estimated by using Eq. (3.1) based on the performance of two pilot subjects, where n_1 and n_2 denote number of observations at the two levels of the examined factor; $\overline{\mu}_1$ and $\overline{\mu}_2$ denote the corresponding performance means of the two levels. The population variance (σ) was estimated as the standard error based on the residuals after fitting the data to a model in the evaluated factor. Based on these estimates, the least significant number (N) of observations necessary to distinguish the difference between the two levels of the examined factor was determined at the significance level of α=0.05 and with a power ($1\text{-}\beta$) greater than 0.8. After that, the minimum number of participants was calculated by dividing N by 8 trials and 6 observations in a trial (see the descriptions of data collection in Section 3.1.6). This number was then rounded up to the nearest integer.

$$\delta^2 = \frac{n_1(\overline{\mu}_1\text{-}\overline{\mu})^2 + n_2(\overline{\mu}_2\text{-}\overline{\mu})^2}{n_1+n_2} \tag{3.1}$$

The pilot test observations also aided in establishing the timing of delivery of secondary tasks. Based on the performance of the two pilot subjects, an appropriate task

loading was defined to ensure sensitive assessment of the distraction effect without overloading. It was found that subjects typically needed a 5-second interval to respond to cognitive questions and they could answer probe questions approximately every 25 seconds without compromising driving and secondary tasks performance.

Based on the pilot tests, 20 participants were recruited for the formal tests. As it has been observed that young drivers are more likely to be involved in distraction-related crashes than older drivers (Stutts, Reinfurt, Staplin, & Rodgman, 2001), the current study only included young drivers between 18 and 21 years of age (M=18.8 yrs, SD=1.4 yrs) and having driving experience between 0.5 and 4 years (M=2.45 yrs, SD=1.62 yrs). The recruitment of subjects was balanced for gender. All participants were required to have a valid driver license and normal vision without correction. In this experiment, no hearing or cognitive tests were conducted to assess participant audition and cognitive abilities. However, participant performance data from the training trials, including the visual and cognitive distraction tasks were used to confirm hearing and cognitive processing abilities, in general (see Section 3.1.7). Participants were compensated at a rate of $15/hour to provide incentive for performance in the simulation. Based on prior research studies conducted with subjects from a similar population, no additional incentive or reward was considered necessary to motivate participants to follow the experiment instructions.

3.1.3 Experiment design

The full experiment followed a $2 \times 2 \times 2$ factorial design with two primary driving tasks, including following and passing, two levels of visual distraction (with and without), and two

levels of cognitive distraction (with and without). In total, there were eight experimental conditions to which each participant was exposed. Each trial was 8 minutes in duration and presented one experimental condition. Table 3-1 summarizes the experimental condition combinations and provides a sense of what each driver experienced.

Table 3-1. Experimental Conditions

	Cognitive distraction off		**Cognitive distraction on**	
Primary Tasks	Visual distraction off	Visual distraction on	Visual distraction off	Visual distraction on
Following	FB	FV	FC	FS
Passing	PB	PV	PC	PS

Note: F stands for following; P stands for Passing.
B stands for no distraction (i.e., baseline); V stands for visual distraction only;
C stands for cognitive distraction only; S stands for simultaneous distraction condition.

3.1.4 Primary tasks

All participants performed the two types of driving tasks on a simulated interstate-style highway. The highway configuration included two lanes in each direction and a green grass median dividing the two directions. Traffic was presented in both directions for the duration of the simulation (on average 10 vehicles/minute/lane). The roadway was equipped with conventional roadway signs. In addition, dynamic message signs (DMSs) were designed to enrich visual cues in the driving environment. To better discriminate glances to the roadway from the visual distraction task display, all the DMSs were overhead signs. Trees also populated the simulation environment to provide additional perceptual cues.

Both types of driving tasks required participants to monitor lead vehicle maneuvers and react to them by changing lanes. Although the two driving task types consisted of similar driving operations, they were expected to require different cognitive processes. Both

following and passing tasks required participants to maintain vehicle speed as close as possible to predefined limits. The speed limits changed six times between segments of roadway during each driving scenario and included 55 mph and 65 mph. Lead vehicle behaviors requiring driver responses did not commence until 45 seconds into a simulation trial and ended at least 15 seconds before a participants' vehicle crossed a finish line. In addition, participants were required to comply with all roadway regulations, and pay attention to overhead signs, including highways signs and DMSs. Any violation of regulations in responding to lead vehicle behavior was recorded as a basis for the experiment data screening process.

In the following task, there was only one lead vehicle, which changed lanes 12 times during a test trial. Participants were required to maintain a safe distance from the lead vehicle and change lanes when the lead vehicle did so. The intervals between two consecutive lane changes were randomly selected between 20 and 40 seconds.

In the passing task, participants were instructed to maintain their vehicle in the right lane while monitoring a lead vehicle in front of them (within 80 ft). When the lead vehicle decelerated to 10 mph below the speed limit or more, participants were required to pass the lead vehicle and return to the right lane. They then followed a new lead vehicle in the right lane until that vehicle decelerated and so on. When driving, participants were required to avoid collisions with other vehicles on the road, traveling either above or below the speed limit. Six passing conditions were posed in each trial with a random interval of 45 to 65 seconds between two consecutive passing maneuvers. To promote the fidelity of simulated tactical driving scenarios, there were motor vehicles traveling either above or below the

speed limit when drivers attempted make passes. Drivers encountered three traffic patterns during passing, similar to real-world situations, including: 1) no traffic interference with the passing maneuver; 2) a slow vehicle appeared in the adjacent lane that interfered either from the side or front of the driver's vehicle; and 3) a fast vehicle appeared in the adjacent lane that interfered either from the side or behind the driver's vehicle. Except in the first situation, drivers had to make strategic decisions regarding when to initiate passing and how to pass the lead vehicle safely. These three passing conditions randomly occurred throughout all eight test trials. All participants had equivalent exposures to all three conditions. Table 3-2 summarizes the events in each type of driving task, the required levels of driving control, and the expected SA requirements.

Table 3-2. Primary task design: following and passing

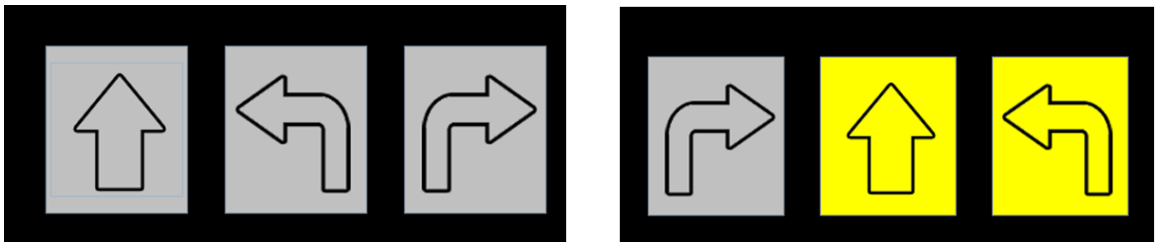
	Following	Passing
Action initiation	Lead vehicle changes lane	Lead vehicle decelerates
Change to left lane	6 times	6 times
Change to right lane	6 times	6 times
Interval	20~40 s (average 30 s)	45 s~65 s (average 60 s)
Levels of driving control		
Monitoring	Operational	Operational
Maneuvering	Operational	Operational; Tactical
Types of SA required		
Monitoring	Level 1	Level 1 & Level 2 (Relative speed)
Maneuvering	Level 1 & Level 2	Level 1, Level 2 & Level 3

3.1.5 Secondary tasks

The two secondary tasks were designed to pose clearly distinguishable visual and cognitive distractions. According to MRT (see Section 1.2.1), the visual distraction task, was expected to only influence the perception stage of information processing and to require focal vision. The response to the visual distraction task was a manual operation, posing no demand

on working memory. The cognitive distraction task was designed to affect driver thinking, including the use of working memory for spatial encoding of roadway information. The task was delivered verbally to minimize the influence on visual perception and required a verbal response in order to minimize the motor control requirement. In addition to fulfilling requirements derived from MRT, the distraction tasks resembled certain aspects of common in-vehicle devices, such as an in-vehicle navigation aid or on-line roadway assistance system. Both tasks were delivered from 15 seconds into a simulation trial until 15 seconds before the end of a trial. The design of the two distraction tasks is described in the following passage.

The visual distraction task included a visual interface similar to an in-vehicle navigation aid. Prior visual distraction studies (Engström et al., 2005; Liang, 2009) and the elements of current in-vehicle navigation systems were used as references in designing the task. The interface displayed three arrows pointing in different directions. Participants were required to detect a target arrow (pointing upward) with a yellow background among distracter stimuli, comprising all other directional arrows with gray or yellow backgrounds. The visual display was updated every 10s and the locations of target and distracter arrows were randomized. A target arrow might not appear in every update. Participants were required to act on the display when that target arrow condition was presented. The distraction interface was considered active when two-out-of-three arrows were highlighted with yellow backgrounds, which always included an upward pointing arrow (see Figure 3-2 (b)). The inactive condition was when all arrows had a gray background (see Figure 3-2 (a)). Once the display was active, participants were supposed to use a stylus to touch the upward arrow.



(a) Task does not require a manual response (b) Task requires a manual response

Figure 3-2. Illustrations of the visual distraction task interface.

Similar to a task used by Liang study (2009), the cognitive distraction resembled auditory instructions from an on-line navigation aiding system, such as the OnStar* system by GM. The auditory messages described the path of a car traveling on a controlled-access highway loop (see Figure 3-3). The loop was defined as octangle in shape, with exits in cardinal and marginal directions, including south, southeast, east, etc. The virtual car entered the loop at an identified exit and then traveled in either a clockwise or counterclockwise direction. Participants were asked to identify the direction in which the car was headed after passing a certain number of exits. An example auditory message was, “Starting from north, go clockwise, and pass one exit.” The answer to this example would be East. A pool of 30 auditory messages was developed for the experiment. A female experimenter prerecorded all 30 messages in her natural voice. The sequence of the auditory messages was randomized within a trial. The cognitive distraction task was delivered every 20 seconds. Each message was approximately 5 seconds in duration, and participants were given 15 seconds to respond.

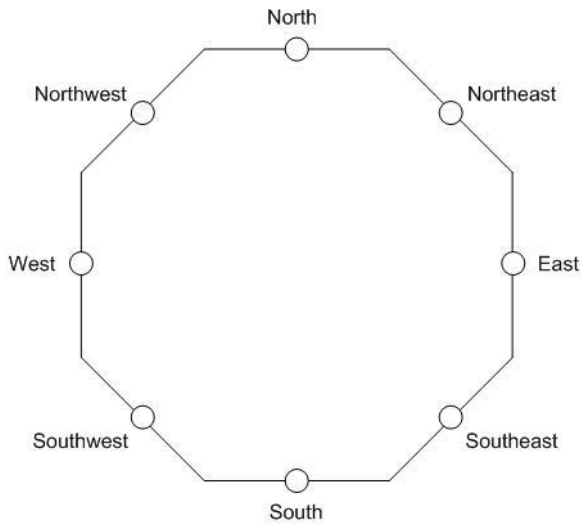


Figure 3-3. The map used in the cognitive distraction task.

3.1.6 Data collection

Task segments

As illustrated in Figure 3-4 simulator performance and eye-tracking measures were recorded in segments. Each experiment trial was divided into maneuvering and monitoring segments. The maneuvering segments started when a lead vehicle decelerated in the passing task or steered right or left in the following task. A maneuvering segment ended when a subject's vehicle traveled 80 ft. after returning to the right lane in passing or after changing to the target lane in following. All other periods, which did not involve maneuvering, were considered as monitoring segments. There was a single data point recorded for each response measure in each segment. These data points represented the average values for the driving performance and eye-tracking measures within a segment. In order to balance the number of recorded data points between the two primary tasks, only the monitoring segments before

lane changes to the left and the maneuvering segments from the right to left lane were used in analysis of the following task, while all the data points on the passing task segments were used in statistical analysis. Unlike driving performance and eye gaze data, driver response accuracy to real-time SA probes was averaged across all segments in a trial. The workload measure (NASA-TLX) was captured only once at the close of each trial representing a specific experiment condition. Therefore, instead having six observations per test trial as overt behavior measures, there was only one observation per test trial for internal metrics.

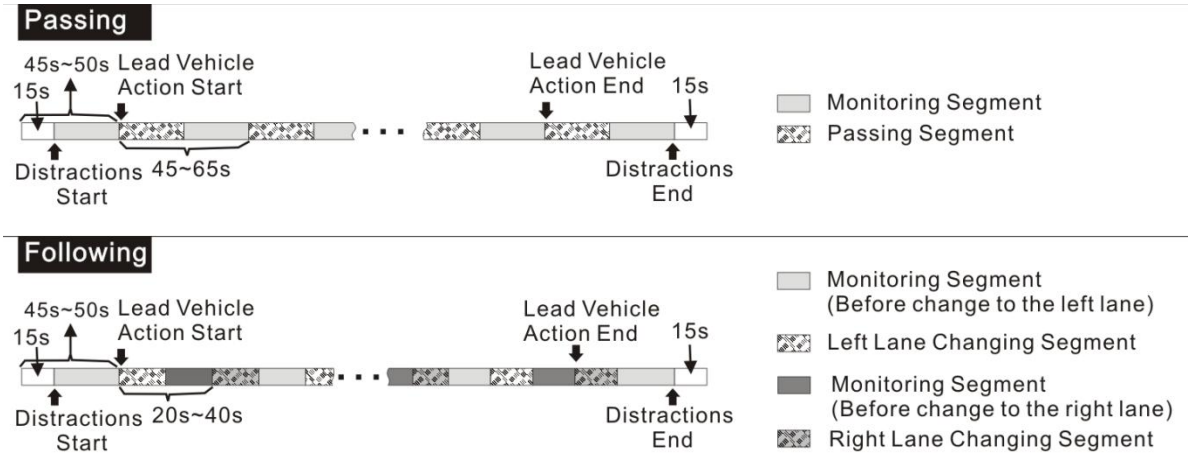


Figure 3-4. Scheme of data collection segments during test trials

Dependent variables

There were four principal groups of dependent variables, including the driver performance measures, real-time SA probes, eye-tracking measures, and NASA-TLX workload scores. Driving performance measures included safety margin, steering entropy, lane maintenance, speed control, and passing and following performance. Driving safety margin was represented by headway distance, headway time, and time-to-collision between the lead vehicle and subject vehicle during monitoring periods (Fuller, 1981). The minimum

values of these three measures within each following segment were used to represent driver decision making regarding safety margin. Headway distance measured the distance between the rear bumper of the lead vehicle to the front bumper of a driver's vehicle. The headway time was calculated by dividing headway distance by the instantaneous speed of a drivers' vehicle; while the time-to-collision was calculated by dividing headway distance by the relative speed between a driver's vehicle and the lead vehicle. A smaller value was indicative of a reduced safety margin in following or passing and riskier driver behavior. Steering entropy described how smoothly participants maneuvered their vehicle while driving, and was calculated as the absolute difference between the second-order Taylor series expansion prediction of steering angle and the observed angle (Nakayama, Futami, Nakamura, & Boer, 1999). A smaller value indicated smoother steering wheel control and less aggressive control. Lane maintenance was represented by variability (standard deviation) in lane position relative to the average lateral position. The measures used to assess speed control included speed variance and speeding percentage. Speed variance was calculated as the variability in speed relative to the ongoing speed limit. Speeding percentage was the percentage of time a driver's vehicle traveled above the speed limit. Steering entropy was recorded for both monitoring and maneuvering segments. All other performance measures were only recorded when drivers performed monitoring tasks.

Passing and lane-changing performance were measured in terms of driver reaction time to lead vehicle decelerations or lane-changes and the time required for drivers to successfully complete passing and lane-changing maneuvers. Reaction time was calculated as the difference between the time a lead vehicle began to decelerate or change lanes and the

time at which a driver's vehicle passed the lane divider. The completion time for a passing maneuver was calculated as the duration from when the lead vehicle began to decelerate to the point when the geometric center of the subject's vehicle returned to the center of the right lane after passing; while completion time for lane-changing during the following task was calculated from the time the lead vehicle began to pass the lane divider until the geometric center of the subject's vehicle returned to the center of the target lane.

Given the need to assess changes in driver internal SA states or SA in the presence of distractions, real-time probes were used to evaluate driver perception, comprehension and projection under each driving condition. The analysis of the influence of visual and cognitive distractions on driver SA followed Endsley's (1995b) three-stage SA model. Interpretations of results were made in terms of Bellet's model defining implicit, explicit and reflexive SA (Bellet et al., 2009). SA probes were derived from a GDTA based on the primary driving task requirements. The correctness (accuracy) and reaction times (latency) of subject answers to probes were identified through retrospective analysis of experimenter notes, videos of experiment trials, and scenario playback using the driving simulator. The complete set of probes, based on the GDTA and used in the experiment, is presented in the Appendix.

Visual behavior measures, describing driver perception, were used to supplement the SA measures. Two visual AOIs were defined in the virtual driving environment, including an on-road AOI and off-road AOI. Glances to the visual distraction task interface (or in-vehicle navigation system) were considered to be within the off-road AOI. Driver eye glance patterns were measured by four metrics, including off-road glance frequency, average off-road glance duration, 95th percentile off-road glances duration, and the percentage of off-road glances.

The off-road glance frequency was represented by the number of off-road glances in a 1-minute period. The percentage of off-road glances was calculated by dividing the summation of the off-road glance durations in an experiment phase by the phase duration. The four eye-tracking measures were collected for both monitoring and maneuvering segments.

Overall NASA-TLX scores were used to assess participant workload under each experiment condition. Driver ranks of workload demand components were recorded after the driving task training and before test trials. Ratings on demand components were collected after each trial. The TLX score is a rank-weighted sum of ratings across six demand components (mental, physical, effort, temporal, frustration, and performance) with the sum scaled to the range from 0-100 (see Eq. (3.2); Hart & Staveland, 1988).

$$TLX\,(Score) = \sum_{i=1}^{6} w_i x_i \tag{3.2}$$

where w_i denotes the weight for one dimension, calculated based on the number of votes for the dimension in pair-wise comparisons among dimensions divided by 15 (i.e., number of unique pairs of dimensions); and x_i denotes the score of the corresponding dimension, measured using a 100 mm line scale with 20 equal intervals and anchors of “Low” and “High”.

3.1.7 Experiment procedure

The procedure for the experiment was divided into four parts: an introduction, a training session, eight experiment trials, and a debriefing. The detailed procedures were as follows:

Introduction

1) Participants completed an informed consent form, which included a brief preview of the current research, participation requirements, potential risks and the compensation policy.
2) A simulation sickness questionnaire (SSQ) was administered before the training session to obtain subject pre-exposure scores in terms of degree of nausea, disorientation, and ocular-motor disturbance (Kennedy, Lane, Berbaum, & Lilienthal, 1993). These scores were used for comparison with post-trial SSQs during the course of the experiment in order to evaluate whether participants were developing symptoms of motion-like sickness. (Fortunately, there were no cases of motion sickness symptoms observed during the entire experiment.)
3) Participants were shown the driving simulator setup and instructed to adjust the simulator seat to accommodate their height.

Training

4) A training session provided participants with an exhaustive overview of the functionality of the simulator and all of the conditions to which participants were to be exposed during the course of the experiment. The session began with training trials on the two primary driving tasks. Each lasted for about four minutes. All participants were trained to meet performance criteria in the primary driving tasks. They were expected to be able to maintain a headway distance of no further than 150 ft when following a lead vehicle and to be able to pass a lead vehicle within 45 seconds. Some participants took longer than 4 minutes to achieve these

criteria and they were permitted additional trials to do so. In general, the training trials provided participants with an opportunity to experience driving in the simulator and to ask questions about how to use the simulator. If participants did not meet the training criteria, they were not permitted to go on to formal testing.

5) After training on the primary tasks, participants were introduced to the real-time SA probes. An experimenter posed participants with probes at regular intervals during the experiment trials (every 25~30 seconds), while participants drove in the following or passing scenarios. Participants were instructed to respond to these questions as quickly and accurately as possible.

6) The training on the secondary tasks familiarized participants with the visual and cognitive distractions in a step-by-step manner. First, participants interacted with the visual distraction display presented on the tablet PC by using the stylus. Next, participants were presented with an eight-exit highway map as part of the cognitive distraction task, and they listened to a set of example auditory messages. Subsequently, they performed the cognitive distraction tasks. They were permitted to retain the map until they were familiar with the general highway layout and nature of the task. Each participant was then required to give answers to several auditory messages by using their internal mental map and not the physical printout. Once participants felt confident about answering the cognitive distraction task questions, training in the simultaneous distraction situation was administered. In general, the cycle time for the visual distraction task was half that for the cognitive distraction task. As a performance criterion for each

distraction task, participants were required to accurately react to five consecutive distraction events and to demonstrate sufficient perception and cognitive capability.

7) Participants were then provided with a comprehensive training trial, which lasted for 8 minutes. They were required to drive in a simulated following scenario, respond to both distraction tasks and answer SA probe questions. A post-SSQ was administered at the end of the training session, and changes in the response measures (sickness symptoms) were noted, if any.

8) Finally, the NASA-TLX workload assessment questionnaire was introduced to participants. They were provided with an overview of the six demands of interest, i.e., mental demand, physical demand, temporal demand, performance, effort and frustration; and their impact on workload. They were instructed on how to rank and rate the demand components, and they made pair-wise comparisons of the demands in terms of their perceived importance to the primary driving tasks (as trained).

Experiment trials

9) After a short break, participants wore the head-mounted eye-tracker system. A standard calibration procedure was carried out prior to the experiment trials. Once the eye-tracker calibration was complete, the eight experimental trials were conducted according to a predefined order (for each subject based on the Latin Square design).

10) Each test trial lasted for approximately 8 minutes. A workload assessment questionnaire was administrated at the end of each trial. Additional SSQs were administrated after every other trial for a total of four times during the experiment. In addition to completing the SSQs, participants were advised to inform the experimenters in the event of occurrence of any discomfort or motion-sickness like symptoms. There was a short break at the end of the fourth trial to address the potential for motion sickness and subject fatigue. Following the break, and after each trial, an eye-tracker re-calibration was carried out to ensure accuracy in the collection of eye-gaze data. Videos were recorded on all experiment trials, which served as a basis for determining participant response times to SA probes and to assess the accuracy of participant responses.

11) Finally, the experimenter thanked participants for their participation and addressed any questions subjects might have regarding the goals or the expected outcomes of the study.

3.2 Experiment Data Analysis

Prior to any statistical modeling, data screening was conducted in order to identify outliers in the response measures due to equipment problems or possible failure of subjects to follow instructions. Specifically, with respect to SA metrics, the latency of SA probes was determined retrospectively by using the audio track of the video recordings of the test trials. The equipment for video recording was placed behind participants while they sat in the simulated vehicle cab, and sometimes the equipment did not clearly capture participant

utterances. For this reason, three out 160 expected observations on SA latency were missing from the experiment data set.

The quality of the eye tracking measures also depended on the data recording process. On occasion, participants accidently touched or bumped the eye tracker device while driving. This disrupted or led to errors in the data collection. In these cases, some glance frequency and dwell time observations were removed from the experiment data set.

Exclusions of observations on driver performance from the experiment data set were largely due to a lack of driver compliance with experiment instructions, resulting from conservative driving styles. For example, in the passing task, some participants only changed lanes when they perceived a large gap in surrounding traffic. As a result, a participant might have waited 1.5 minutes or more to make a passing maneuver while "the new lead vehicle" also decelerated. Consequently, they would pass two lead vehicles together, which resulted in a missing observation for the passing trial. Other examples included participants forgetting to make passes in a passing trial or to strictly follow the lead car in a following trial during testing. In these cases, drivers needed to either quickly accelerate and catch up with the new leading vehicle or decrease their speed and fall back behind the lead vehicle, which resulted in invalidation of some of the driving performance measures. All other data considered to accurately reflect driver external behavior and internal processes were included in statistical analyses. The experiment results are summarized in the subsections below.

Data screening was thus necessary as a basis for removing potential outliers that might introduce spurious variance in responses. After preliminary data screening, data

validation for parametric testing was conducted using normal probability plots, a normality test (Shapiro-Wilks test) and tests for homogeneity of variance (Bartlett statistics).

For any type of response with multiple measures (e.g., driving performance and eye-tracking), a principal component analysis (PCA) was conducted to identify those measures with the greatest degree of variability, which might have been more sensitive to the experiment factor manipulations. After data validation and reduction of the response data sets, multivariate analyses of variance (MANOVAs) were conducted on the remaining measures to account for potential inter-correlations among response measures in identifying significant effects of independent variables on a combination of response measures. Any factors identified to be insignificant in the MANOVAs were excluded from analysis of variance (ANOVA) models. This procedure was followed in order to reduce the possibility of such factors proving to be significant in univariate analyses simply by chance. Inclusion of insignificant factors in an ANOVA may also reduce the error degrees of freedom and sensitivity for detecting significant effects of other influential factors. Consequently, MANOVAs were conducted on the set of performance measures, eye-tracking measures, and SA measures, identifying specific effects of the experimental manipulations on these responses sets. For example, it was expected that the off-road glance frequency and glance duration would be the most sensitive eye-tracking measures reflecting the distraction manipulations, i.e., influence of visual distraction and cognitive distractions in driving. However, the types of primary driving tasks, tactical or operational, were not expected to yield differences in driver gaze.

After the MANOVAs, ANOVAs were conducted on any significant main effects and interaction effects revealed by the MANOVAs across response measures. For further analysis of significant effects, multiple comparison procedures (e.g., Tukey's Honestly Significant Difference HSD test) were performed on significant interactions to identify significant differences among conditions, which were determined by more than two experimental manipulations. Those response measures, which were significantly influenced by the experiment manipulations, were subsequently used as a basis for developing machine learning algorithms to classify driver states of visual and cognitive distractions. The detailed steps as part of the classification step are discussed bellow.

3.3 Classification of Distraction States

The classification procedure was developed based on the experiment observations. This study focused on three classification problems, including detecting visual distraction regardless of cognitive distraction, detecting cognitive distraction regardless of visual distraction, and detecting integrated visual and cognitive distraction. With respect to the first problem, without driver visual perception of the environment, situated cognition cannot occur. That is, driver comprehension and projection of the roadway situation may not occur in the absence of visual attention. The current study applied visual distraction classification in operational and tactical control separately and jointly (i.e., across the two types of driving tasks). This step relied on eye-tracking measures, which have proved to be sensitive for revealing changes in driver perception with and without the presence of a navigation aid.

The next problem was to classify driver cognitive distraction regardless of visual distraction. Because of the apparent high dependence of driver tactical control on high-level cognitive processes (e.g. correctly formulating SA; Jin and Kaber, 2009), it was expected that cognitive distraction might be more detrimental in tactical driving control as compared with operational driving. That is, cognitive distraction was expected to more likely result in degraded driving behavior, increased workload and degraded SA in tactical driving control compared to operational control. Related to this, cognitive distraction was expected to be identified with a higher accuracy (85% or above based on prior work) in tactical driving control.

Based on the solutions of the prior two classification problems and the experiment result, two strategies have been developed to accomplish the integrated classification of visual and cognitive distraction. The first alternative uses a "two-step" classification procedure, which classifies visual distraction with all eye-tracking measures first, followed by classifying cognitive distraction. The second alternative uses a "direct mapping" approach, which assumes visual, cognitive, and dual distraction conditions all led to unique behavior consequences.

The evaluation criteria for the classification models included metrics focused on both overall performance of the learning algorithm for all classes of distraction and the effectiveness of the classifier for a single class (Japkowicz & Shah, 2011b). The overall accuracy of the classifier was calculated as the number of data entries correctly classified divided by the total number of entries. Cohen's κ (kappa) statistics were also calculated to account for the possibility that correct classification was a result of mere coincidental

concordance between the classifier output and "true states" (Cohen, 1960) of driver distraction. Cohen's κ was calculated as formula (3.3).

$$\kappa = \frac{p_0 - p_e^C}{1 - p_0} \tag{3.3}$$

where p_0 denotes the overall classification accuracy, and p_e^C denotes the chance agreement. Given $Y_{p,j}$ represents the number of data entries that actually belong to class *j*, $f_{p,j}$ represents the number of entries classified as class *j* and *m* represents the total number of data entries, the p_e^C can be identified as $\sum_j Y_{p,j} \cdot f_{p,j} \big/ m$. In general, a greater value of κ corresponds to better performance of a classifier. A κ value greater 0.75 can be generally considered as a criterion of high agreement between the true labels of data entries and classifier estimations.

Related to the objective of the current study, signal detection theory (SDT) was used to assess the performance of a SVM from a single class perspective (Green & Swet, 1988). There are four potential outcomes of SDT including: 1) a hit, when the presence of a target distraction is correctly identified; 2) a miss, when the presence of a target distraction is not identified; 3) a false alarm, when a target distraction is absent but is identified as present; and 4) a correct rejection, when a target distraction is absent and is not identified as present. In this study, the target distraction was either visual or cognitive in specific classification problems. For example, a visual distraction was the target for the visual distraction classification problem. It is worth noting that the integrated distraction classification problems involved multiple types of distraction targets. The evaluation criteria for a specific

approach were expanded based on the potential outcomes of a specific classification approach.

Finally, sensitivity analyses were applied to the classification process incorporating SVMs in order to assess how uncertainty in model inputs might influence model outputs (Sltelli, Tarantola, Campolongo, & Ratto, 2004). The results of the sensitivity analysis were used to compare the influence of each input feature in predicting driver distraction states. The sensitivity analysis involved a feature-based sensitivity of posterior probabilities (FSPP) technique (Shen, Ong, Li, & Wilder-Smith, 2007). This technique calculates the aggregate value (across the feature space) of the absolute difference of the probabilistic output of a SVM with and without the feature. A larger difference in Platt's Probabilistic output, due to exclusion of a single feature, indicates a greater influence of that feature in predicting distraction states (Platt, 1999, 2000). The Platt's Probabilistic output of a model was calculated using Eq. (3.4) as shown below:

$$FSPP_i = \frac{1}{N}\sum_{j=1}^{N}\left|\hat{p}(c \mid x_j) - \hat{p}(c \mid x_{(i),j})\right| \tag{3.4}$$

where N represents the total number of observations in the classification problem. The indicator *c* represents the states that are positively classified by the model (e.g., the distracted states in the proposed study). The quantity $\hat{p}(c \mid x_j)$ refers to the estimated posterior probability of belonging to class *c* given the input vector x_j for the data point *j* (including all input features); while $\hat{p}(c \mid x_{(i),j})$ refers to the estimated posterior probability of belonging to

class *c* given feature *i* is excluded from the input vector for data point *j*, which is denoted as $x_{(i),j}$.

In the current research, all the SVM classification processes were performed using the "e1071" SVM package, which is essentially an interface to the "LIBSVM" (Library SVM) developed in R language (Dimitriadou et al., 2011; Karatzoglou et al., 2006). "LIBSVM" is an award-winning implementation of SVM formulations, including the most common SVM kernels (Chang & Lin, 2007; Hsu et al., 2003), as described above. In addition to having model tuning functions such as grid-search and cross-validation, "LIBSVM" also provides probability values for predictions.

CHAPTER 4 EXPECTED OUTCOMES

The present study examined the effects of visual and/or cognitive distraction on driver behavior and operational and tactical driving performance. The following outcomes were expected from the study:

1) Identification of characteristics of visual and cognitive distraction tasks that have unique influences on driver cognitive processes and can be applied in similar research to evaluate driver behavior and performance;
2) Quantification of the influence of different modalities of distractions on driving behavior at operational and tactical levels of control, by using both overt behavior measures and internal process indicators;
3) Assessment of the sensitivity and validity of real-time probe techniques in driving-related research for predicting performance and driver distraction state classification;
4) Development of a classification algorithm to effectively identify driver visual and/or cognitive distraction states that apply to operational and tactical driving separately and jointly; and
5) Identification of a set of overt and internal driver behavior measures that are most predictive of states of distraction at the different levels of control.

CHAPTER 5 EXPERIMENT RESULTS

5.1 Situation Awareness

Both latency and accuracy of driver responses to SA probes were subjected to ANOVAs, although some responses required transformation. An arcsine transformation was applied to the accuracy of Level 1 SA (based on Endsley's (1995b) prior research); a square root transformation was applied to the response latency of Level 1 SA and the accuracy of Level 2 SA; and a logarithmic transformation was applied to the response latency of Level 2 and Level 3 SA.

ANOVA results revealed significant effects of primary task type ($F(1,133)=8.78$, $p=0.004$), visual distraction ($F(1,133)=16.61$, $p<0.001$), a two-way interaction of primary task and cognitive distraction ($F(1,133)=3.96$, $p=0.049$), a two-way interaction of visual and cognitive distraction ($F(1,133)=8.93$, $p=0.003$), and a three-way interaction (all main effects; $F(1,133)=24.0$, $p<0.001$) on the response accuracy for Level 1 SA probes. ANOVA tests also revealed significant effects of primary task type ($F(1,130)=8.14$, $p=0.005$) and cognitive distraction ($F(1,130)=5.69$, $p=0.019$), as well as a two-way interaction of primary task and visual distraction ($F(1,130)=6.10$, $p=0.015$) and a two way interaction of visual and cognitive distraction ($F(1,130)=6.68$, $p=0.011$) on response time of Level 1 SA. Comparison of results between the two primary tasks suggested driver dependence on Level 1 SA varied. To better interpret the higher-level interactions, ANOVA models were applied to the two primary tasks, separately.

With respect to the following task, results indicated significant effects of visual distraction on response accuracy ($F(1,57)=6.08$, $p=0.017$) and latency for Level 1 SA probes ($F(1,57)=6.72$, $p=0.012$), cognitive distraction on response latency ($F(1,57)=9.2$, $p=0.004$), and a two way interaction of visual and cognitive distraction on response accuracy ($F(1,57)=29.73$, $p<0.001$) and response latency ($F(1,57)=10.87$, $p=0.002$). Post-hoc analysis using Tukey's test (see Figure 5-1) revealed drivers to have the lowest accuracy Level 1 SA in following tasks when no distraction was present. This was significantly different from the visual distraction only and cognitive distraction only conditions. Explanation of these results is offered later in the discussion section (see Section 5.6). Simultaneous distraction led to lower response accuracy as compared to visual distraction. Tukey's test also showed that drivers took a longer time to respond Level 1 SA queries under dual-distraction compared to other conditions. For the passing task, only visual distraction had a significant influence on Level 1 SA probe response accuracy ($F(1,57)= 10.01$, $p=0.003$). Contrary to expectation, drivers showed higher response accuracy with visual distraction than without (86% $\pm$15% vs. 75% $\pm$15%).

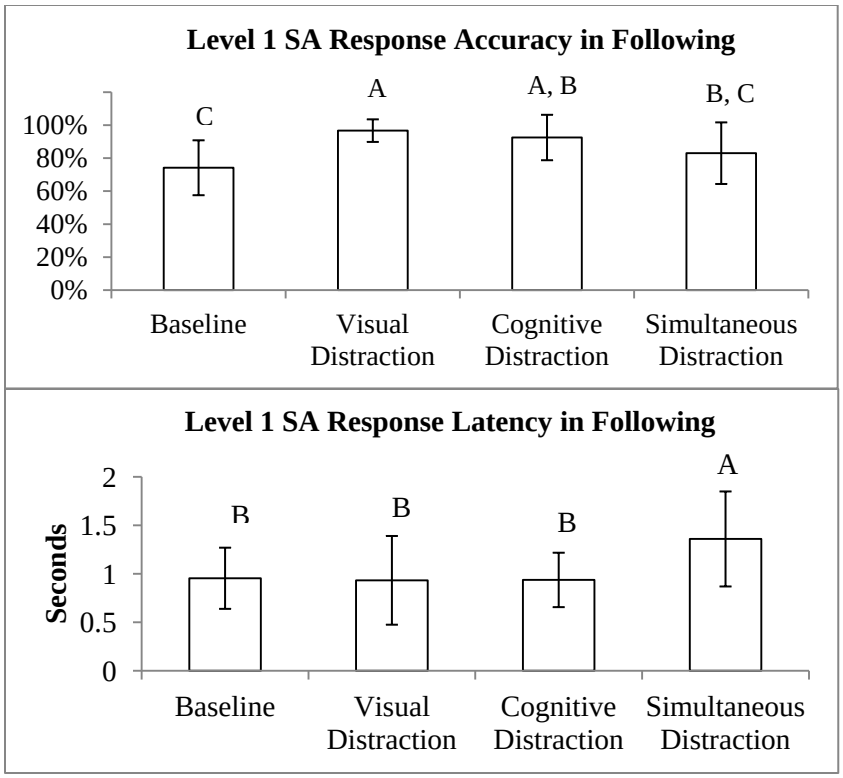


Figure 5-1. Tukey's test results on Level 1 SA in following tasks

Similar to Level 1 SA, a significant three-way interaction of primary task type, visual distraction and cognitive distraction was observed for Level 2 SA response accuracy ($F(1, 130)= 7.21$, $p=0.008$); and a significant two-way interaction of primary task type and visual distraction for Level 2 SA latency ($F(1, 130)= 15.6$, $p<0.001$). Hence, separate ANOVAs were conducted for the two primary tasks. For the following task, results revealed a significant two-way interaction of visual and cognitive distraction on both response accuracy ($F(1,57)=6.31$, $p=0.015$) and response time ($F(1,57)=10.44$, $p=0.002$). However, neither visual distraction nor cognitive distraction alone showed significant main effects on Level 2 SA measures. Tukey's tests results indicated that drivers had the most accurate Level 2 SA under the simultaneous distraction condition, which was significantly higher than visual

distraction only, but was not significantly different from no distraction condition (see Figure 5-2). This result is also addressed later in the discussion section (see Section 5.6). Drivers took longer time to respond to Level 2 SA probes under single distraction conditions compared to no distraction. An ANOVA on the passing task responses only showed a significant main effect of visual distraction on response accuracy to Level 2 SA probes ($F(1,57)=31.44$, $p<0.001$) and a significant main effect of cognitive distraction on response latency ($F(1,54)=12.38$, $p<0.001$). Lower response accuracy was observed with visual distraction than without (68% ± 17% vs. 87% ± 14%); while longer response times were associated with the presence of cognitive distractions (1.34 ± 0.59 s vs. 1.04 ±0.45 s). Explanation for the former result is offered in the discussion section.

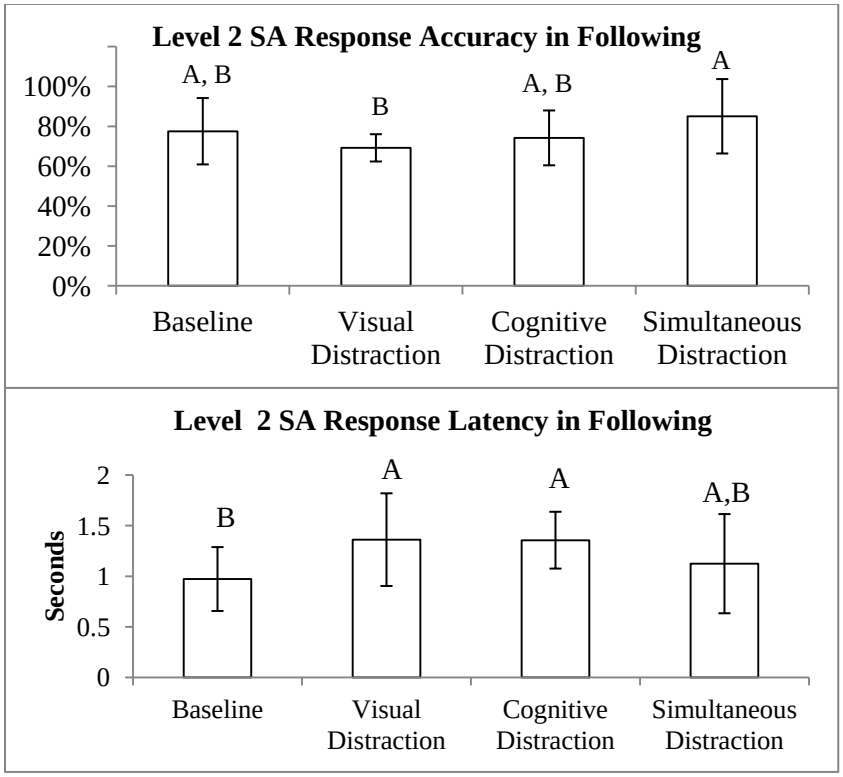


Figure 5-2. Tukey's test results on Level 2 SA in following tasks

For Level 3 SA, an ANOVA model revealed a significant effect of the two-way interaction between visual distraction and primary task type ($F(1,130)=6.50$, $p=0.012$) in terms of response time. Analysis of the following task revealed a significant main effect of visual distraction in response accuracy ($F(1,57)=5.84$, $p=0.019$) and in response latency ($F(1,57)=15.03$, $p<0.001$), and a significant main effect of cognitive distraction in response accuracy ($F(1,57)=16.2$, $p<0.002$) and in response latency ($F(1,57)=9.08$, $p=0.003$). When performing following tasks, drivers showed higher accuracy (83% ± 18% vs. 74% ± 20%) and shorter response times (1.19 ± 0.5 s vs. 1.51 ±0.55 s) with visual distraction compared to none; while they had lower accuracy (71% ± 21% vs. 86% ± 14%) and longer response times with cognitive distraction compared to without (see Section 5.6 for explanations). Analysis of passing task responses revealed a significant main effect of cognitive distraction in response time ($F(1,54)=10.86$, $p=0.002$), and a marginally significant main effect of cognitive distraction on response accuracy ($F(1,57)=3.81$, $p=0.056$). Drivers required greater time to respond to cognitive distraction questions (1.40 ± 0.70 s vs. 1.02 ±0.37 s) and showed lower accuracy (72% ± 20% vs. 79% ± 16%) with cognitive distraction compared to without.

5.2 Driving performance

All eight driving performance measures - speed variance, speeding percentage, lane deviation, headway distance, headway time, time to collision, steering entropy during monitoring and during maneuver period - were included in a PCA. The analysis was applied using a covariance structure for all eight measures. A Varimax-rotation method was used for orthogonal transformation of the factor loadings after estimating original loadings.

According to a PCA conducted on the combined data set for both primary tasks, the first factor included all safety margin measures and accounted for 26.5% of the variability in driving performance (see Table 5-1). The second factor corresponded to lane deviation during monitoring (13.29%); the third component corresponded to speeding percentage (12.37%). Steering entropy of both monitoring and maneuvering segments entered into the forth factor accounting for 7.7% of performance variability.

Similar to the overall PCA, the first factor of the PCA of following task consisted of safety margin measures, including headway distance and headway time (see Table 5-2). Speeding variance still accounted for a large portion of total variance (13.78%), which was represented by the second factor. The third factor consisted of steering entropy during both monitoring and maneuvering segments (7.8%). However, different from the PCA across the two types of driving tasks, the lane deviation was no longer an important source of variation in following tasks.

Table 5-1. PCA results for driving performance across the types of primary driving tasks

	Factor 1	***Factor 2***	***Factor 3***	***Factor 4***
Speed variance	0.064	-0.141	0.083	0.012
Speeding percentage	-0.138	-0.148	**0.972**	-0.122
Lane deviation	-0.047	**0.980**	0.003	0.196
Headway distance	**0.985**	-0.110	0.032	-0.049
Headway time	**0.978**	-0.126	0.031	-0.065
Time to collision	0.384	-0.033	-0.149	-0.087
Steering entropy during monitoring	0.043	0.153	-0.111	0.464
Steering entropy During maneuver period	-0.217	-0.053	0.044	**0.578**
Variance percent by each factor	26.852	13.209	12.371	7.711

Note: Measures in bold are considered highly influential in a principle factor.

Table 5-2. PCA results for driving performance in following tasks

	Factor 1	*Factor 2*	*Factor 3*	*Factor 4*
Speed variance	-0.085	0.182	-0.027	0.016
Speeding percentage	0.002	**0.848**	-0.065	0.145
Lane deviation	-0.067	-0.079	0.154	-0.312
Headway distance	**0.956**	-0.186	-0.095	0.109
Headway time	**0.967**	-0.177	-0.110	0.145
Time to collision	0.288	-0.507	-0.085	**0.410**
Steering entropy during monitoring	0.092	-0.140	**0.571**	-0.232
Steering entropy During maneuver period	-0.194	0.039	**0.491**	-0.053
Variance percent by each factor	24.876	13.788	7.803	4.699

Note: Measures in bold are considered highly influential in a principle factor.

As shown in Table 5-3, the PCA for passing tasks revealed safety margins to be the leading source of variance in performance (25%), followed by steering entropy during monitoring (13.6%). The third principle component of passing task performance included lane deviation and speed variance (8.6%), while the fourth component included time-to-collision (6.67%).

Table 5-3. PCA results for driving performance in passing tasks

	Factor 1	*Factor 2*	*Factor 3*	*Factor 4*
Speed variance	0.104	0.121	-0.350	0.144
Speeding percentage	-0.079	-0.146	-0.275	0.054
Lane deviation	-0.199	0.170	0.636	0.016
Headway distance	**0.947**	-0.070	-0.113	0.216
Headway time	**0.964**	-0.045	-0.132	0.228
Time to collision	0.282	0.006	-0.155	**0.636**
Steering entropy during monitoring	0.013	**0.978**	0.193	0.077
Steering entropy During maneuver period	-0.201	0.244	0.004	-0.036
Variance percent by each factor	25.016	13.601	8.678	6.674

Note: Measures in bold are considered highly influential in a principle factor.

Although the multivariate normality assumption may be relaxed when using PCA for exploratory purposes, the test for adequacy of a factor analysis model remains rigid. There

were only three performance measures that conformed to the normality assumption after translational transformations, including steering entropy during tasks, lane deviation and headway time. Therefore, adequacy of the principle component models could not be achieved through standard procedures. That said, the derived principle components (summarized above) for the following task, passing task, and overall performance only accounted for less than 60% of the total variance in driving performance. Therefore, all the performance measures were included in the task analyses.

5.2.1 Overall driving performance

As mentioned above, only steering entropy during tasks, lane deviation, and headway time conformed with the normality assumption of parametric methods. A MANOVA procedure was used to identify significant independent variables that influenced the pattern of responses across independent variables prior to applying an ANOVA to individual responses. Results revealed significant main effects of primary driving tasks ($F(3,883)=19.84$, $p<0.001$), visual distraction ($F(3,883)=12.62$, $p<0.001$) and cognitive distraction ($F(3,883)=3.69$, $p=0.025$). They also suggested a significant interaction of visual and cognitive distraction ($F(3,883)=4.13$, $p=0.0061$).

ANOVA results on the log transform of steering entropy during maneuvering revealed significant main effects of driving task type ($F(1,901)=29.94$, $p<0.001$) and visual distraction ($F(1,901)=31.72$, $p<0.001$), and a significant interaction effect of visual and cognitive distraction ($F(1,901)=9.67$, $p=0.002$) (With respect to the denominator degrees of freedom in this test statistic, the total number of the observations for steering entropy during

maneuvering was 20 participants * 8 trials * 6 observations/trial = 960. Thirty-two data points were missing due to driver failure to follow instructions. Consequently, the DOFs for error were 960 - 1 (for bias) – 32 (for missing data) - 19 (for subjects) – 7 (for the model) = 901). Drivers showed larger steering entropy when performing passing maneuvers compared to following (0.71 ±0.49 degree vs. 0.63 ± 0.35 degree). As shown in Figure 5-3, drivers produced the largest steering entropy when both distractions were present, followed by visual distraction only. Drivers showed the smallest steering entropy when the cognitive distraction was present, which was significantly lower than when visual distraction or dual-distraction was present. However, the smoothness of steering under cognitive distraction conditions was not significantly different from driving in the absence of any distraction. These results are different than the findings of Liang and Lee (2010). They claimed that cognitive distraction caused decrements in steering smoothness but improved lane maintenance. However, in their experiment, participants were required to press a button in response to the cognitive distraction task. Therefore, reduced steering control action was expected when drivers performed the distraction task. This type of manual response also overlapped the required response to their visual distraction task. Opposite to this, the cognitive distraction task used in the current research only required a verbal response. Not only does this comparison suggest that cognitive distraction may not be influential in steering control, it also indicates that rather than alleviating the influence of visual distraction (Liang & J. D. Lee, 2010), posing cognitive distraction in addition to visual distraction tasks may be most detrimental to steering control.

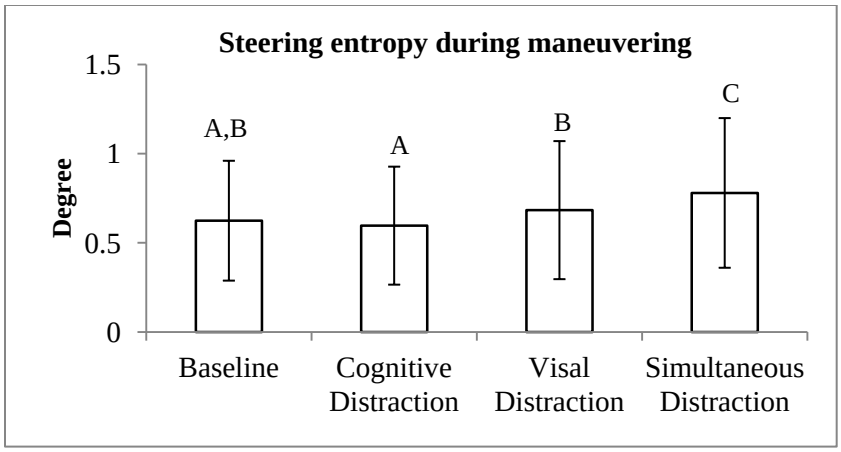


Figure 5-3. Tukey's test results on steering entropy during the maneuvering periods for overall driving performance

Similarly, ANOVA analysis revealed significant main effects of driving task type (F(1,892)=8.6, p=0.003) and cognitive distraction (F(1,892)=6.58, p=0.011), and a significant interaction of cognitive and visual distraction (F(1,892)=5.85, p=0.016) on the log transform of headway time. Drivers allowed larger headway times when performing following tasks compared to passing tasks (1.65 ± 0.97 s vs. 1.47 ± 0.89 s). The largest headway times were observed under visual distraction, which was significantly larger than driving under cognitive distraction and simultaneous distraction (see Figure 5-4).

With respect to lane deviation, only the type of primary driving task was found to significantly influence the square root transform of the response (F(1,896)=20.33, p=0.001). Drivers had large lane deviations during following compared to passing (0.64 ± 0.25 ft vs. 0.60 ± 0.3 ft).

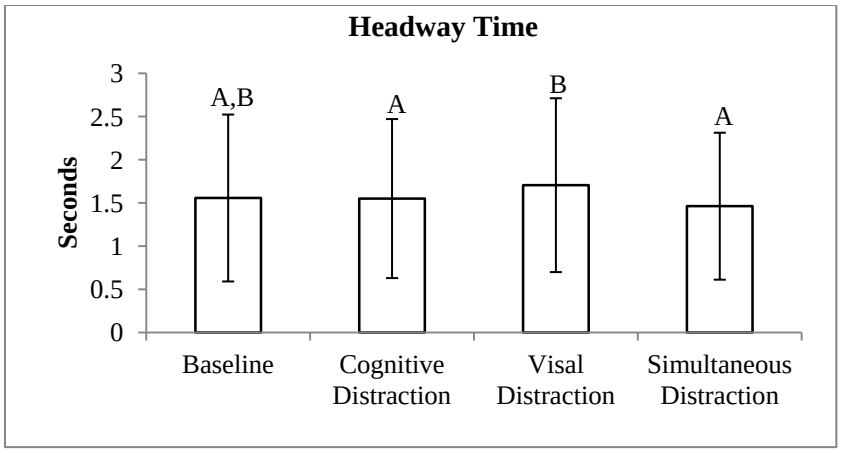


Figure 5-4. Tukey's test results on headway time during monitoring periods for overall driving performance

A Friedman-type non-parametric test was used to analyze those response measures that did not conform to parametric assumptions (Mack & Skillings, 1980). Non-parametric tests revealed a significant main effect of the types of driving tasks on speed variance (MS=121.95, p<0.001), speeding percentage (MS=23.36, p<0.001), headway distance (MS=20.9, p<0.001) and time to collision (MS=285.31, p<0.001). Because Friedman non-parametric tests provide limited capability to explore interaction effects, the two types of primary driving tasks were analyzed separately. Results are presented below.

5.2.2 Operational driving control

Non-parametric tests revealed significant main effects of visual distraction on speed variance (MS=4.6, p=0.032) and cognitive distraction on time-to-collision (MS=4.83, p=0.028). Steering entropy during monitoring phases was also significantly influenced by visual distraction (MS=72.45, p<0.001). Speed variance and steering entropy were significantly higher when driving under visual distraction conditions than none (14.54 ± 3.89

mph vs. 13.9 ± 3.29 mph for speed variance; 0.29 ± 0.19 degree vs. 0.19 ± 0.12 degree for steering entropy during monitoring phases). Drivers tended to allow shorter times-to-collision during monitoring phases under cognitive distractions compared to none (40.49 ± 69.34 seconds vs. 55.68 ± 92.59 seconds for time to collision).

In addition to the driving performance measures mentioned above, reaction times to lead vehicle lane changes and lane change times were analyzed for the following task. An ANOVA on the log transform of reaction times indicated significant main effects of visual distraction ($F(1,431)=4.69$, $p=0.031$) and cognitive distraction ($F(1,431)=8.71$, $p=0.003$), and a significant interaction between visual and cognitive distraction ($F(1,431)=4.52$, $p=0.034$). (With respect to the denominator degrees of freedom in this test statistic, the total number of the observations for reaction time to lead vehicle lane-change was 20 participants * 4 passing trials * 6 observations/trial = 480. Twenty-six data points were missing due to driver failure to follow the course of a lead-vehicle as instructed (e.g., make a lane-change prior to the lead-vehicle change). Consequently, the DOFs for error were 480 - 1 (for bias) - 26 (for missing data) - 19 (for subjects) - 3 (for the model) = 431.) As shown in Figure 5-5, the need to respond to distractions motivated drivers to react quicker to lead car maneuvers for all types of distraction. In addition, ANOVA results demonstrated a significant main effect of visual distraction ($F(1,451)=7.11$, $p=0.008$) and a significant two-way interaction of visual and cognitive distraction ($F(1,451)=4.54$, $P=0.034$) on lane-change completion times. As illustrated in Figure 5-6, visual distraction increased the pace of driver lane-change maneuvers as compared to cognitive distraction.

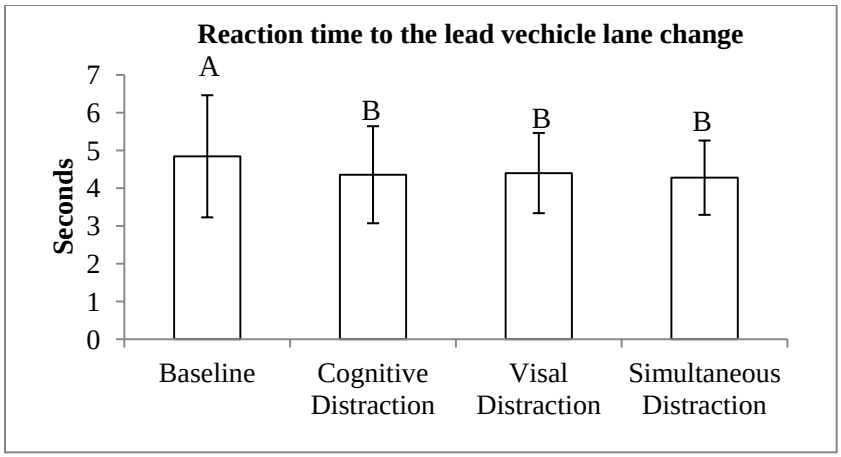


Figure 5-5. Tukey's test results on reaction times to lead vehicle lane changing in following tasks

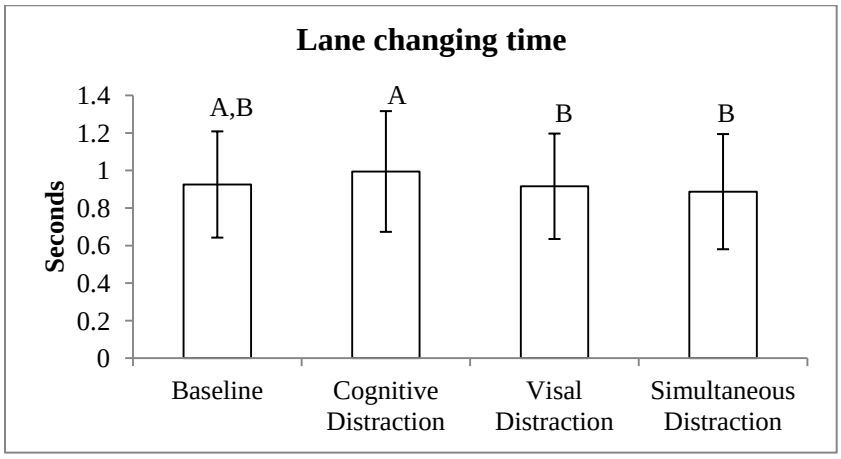


Figure 5-6. Tukey's test results on lane changing times in following tasks

5.2.3 Tactical driving control

Friedman non-parametric analyses revealed significant main effects of visual distraction (MS=17.12, $p<0.001$) and cognitive distraction (MS=12.43, $p<0.001$) on speed variance. Non-parametric analyses also demonstrated a significant main effect of visual distraction on steering entropy during monitoring (MS=20.3, $p<0.001$). Larger speed variances and steering entropy were observed when visual distraction was present (12.54±

6.91 mph vs. 9.95 ±5.02 mph for speed variance; 0.27 ± 0.22 degree vs. 0.19 ± 0.14 degree for steering entropy during monitoring phases). Cognitive distraction was also associated with larger speed variance (12.23 ± 6.5 mph vs. 10.28 ± 5.68 mph). Non-parametric analyses revealed a marginally significant effect of cognitive distraction on headway distance (MS=3.60, p=0.057). Drivers tended to have shorter headway distance under cognitive distraction conditions than other conditions (107.5 ± 62.65 ft vs. 126.25 ± 85.44 ft).

Reaction times to lead vehicle deceleration and passing completion times were analyzed as well. A Friedman non-parametric analysis of passing reaction times revealed a significant main effect of visual distraction (MS=4.44, p=0.035). An ANOVA on the log transform of passing completion time indicated a significant main effect of visual distraction (F (1,403) = 7.77, p=0.006). (With respect to the denominator degrees of freedom in this test statistic, the total number of the observations for reaction time to lead vehicle deceleration was 20 participants * 4 passing trials * 6 observations/trial = 480. Fifty-four data points were missing due to driver failure to make passes as instructed. Consequently, the DOFs for error were 480 - 1 (for bias) - 54 (for missing data) - 19 (for subjects) - 3 (for the model) = 403.) Drivers took longer to react to lead vehicle deceleration with visual distraction (15.52 ± 12.89 seconds and 14.28 ± 14.28 seconds) compared to without. They also took longer to pass lead vehicles under visual distraction conditions than other conditions (15.96 ± 8.17 seconds and 14.16 ± 6.73 seconds).

5.3 Eye-tracking

All eye-tracking measures, off-road glance frequency, average off-road glance duration, 95th percentile off-road glances duration and the percentage of off-road glances, were included in a PCA analysis. According to the PCA results, the variability in driver gaze behavior was represented by four components (see Table 5-4). The first component included off-road glance frequency and off-road glance durations during maneuvering periods. The second component described driver gaze pattern during monitoring periods. The third component was a combination of off-road glance frequency and percentage of off-road glances during monitoring. The fourth factor included off-road glance frequency and percentage of off-road glances during maneuvering. Similar results were also found for independent PCAs on the following and passing tasks (see Table 5-5 and Table 5-6).

Table 5-4. PCA result on eye-tracking measures across types of primary driving tasks

		Factor 1	***Factor 2***	***Factor 3***	***Factor 4***
Monitor	Off-road glance frequency	0.237	0.265	**0.823**	0.203
	Average off-road glance duration	0.216	**0.929**	0.259	0.154
	Percentage of off-road glances	0.237	**0.485**	**0.824**	0.174
	95 percentile off-road glances duration	0.235	**0.761**	0.388	0.123
Maneuver	Off-road glance frequency	0.326	0.173	0.224	**0.902**
	Average off-road glance duration	**0.930**	0.223	0.172	0.145
	Percentage of off-road glances	**0.711**	0.171	0.215	**0.538**
	95 percentile off-road glances duration	**0.841**	0.213	0.241	0.245
	Variance percent by each factor	29.957	23.767	21.969	16.189

Note: Measures in bold are considered highly influential in a principle factor.

Table 5-5. PCA result on eye-tracking measures for the following task

		Factor 1	***Factor 2***	***Factor 3***	***Factor 4***
Monitor	Off-road glance frequency	0.150	0.405	**0.894**	0.118
	Average off-road glance duration	0.177	**0.882**	0.198	0.151
	Percentage of off-road glances	0.149	**0.688**	**0.656**	0.116
	95 percentile off-road glances duration	0.192	**0.847**	0.323	0.089
Maneuver	Off-road glance frequency	0.409	0.180	0.132	**0.814**
	Average off-road glance duration	**0.946**	0.166	0.121	0.070
	Percentage of off-road glances	**0.836**	0.148	0.106	0.448
	95 percentile off-road glances duration	**0.933**	0.187	0.108	0.248
	Variance percent by each factor	34.307	28.126	17.869	12.349

Note: Measures in bold are considered highly influential in a principle factor.

Table 5-6. PCA result on eye-tracking measures for the passing task

		Factor 1	***Factor 2***	***Factor 3***	***Factor 4***
Monitor	Off-road glance frequency	0.270	0.225	**0.777**	0.337
	Average off-road glance duration	0.283	**0.918**	0.221	0.168
	Percentage of off-road glances	0.320	0.425	**0.803**	0.269
	95 percentile off-road glances duration	0.277	**0.792**	0.282	0.175
Maneuver	Off-road glance frequency	0.314	0.222	0.380	**0.842**
	Average off-road glance duration	**0.830**	0.339	0.238	0.190
	Percentage of off-road glances	**0.621**	0.241	0.371	**0.597**
	95 percentile off-road glances duration	**0.815**	0.303	0.290	0.322
	Variance percent by each factor	27.118	25.209	22.495	18.122

Note: Measures in bold are considered highly influential in a principle factor.

Non-parametric analyses of gaze pattern data demonstrated significant main effects of types of driving tasks on all four eye-tracking measures during both monitoring and maneuvering periods. Hence, non-parametric analyses of visual and cognitive distractions were carried-out separately for following and passing tasks, which allowed further exploration of interactions between driver eye behavior and distractions.

A non-parametric analysis of gaze pattern data collected during the following task revealed significant effects of visual distractions on average off-road glance duration during

monitoring phases (MS=317.27, p<0.001) and maneuvering (lane-changing) phases (MS=56.79, p<0.001). The 95th percentile of glance durations were also significantly influenced by visual distraction during monitoring (MS=317.26, p<0.001) and lane-changing phases (MS=56.20, p<0.001). In addition, the percentage of off-road glances during monitoring (MS=319.37, p<0.001) and maneuvering phases (MS=56.2, p<0.001) were significantly influenced by visual distraction. Similarly visual distraction significantly influenced off-road glance frequency in monitoring (MS=319.36, p<0.001) and maneuvering phases (MS=65.01, p<0.001). Compared to no visual distraction, participants showed a substantial increase in average off-road glance duration in monitoring (0.46 ± 0.18 seconds vs. 0.28 ± 0.17 seconds) and lane-change phases (0.38 ± 0.27 seconds vs. 0.08 ± 0.03 seconds) when visually distracted. Substantial increases were also observed for the 95th percentile of glance durations in monitoring (0.89 ± 0.31 seconds vs. 0.31 ± 0.22seconds) and lane-change phases (0.46 ± 0.29 seconds vs. 0.09 ± 0.03 seconds) under visual distraction. Drivers also showed an increase in proportion of off-road glances for monitoring (8.57% ± 4.29% vs. 0.08% ± 0.30%) and lane changing (4.43% ± 6.64% vs. 0.035% ± 0.32%), as well as an increased off-road glance frequency for monitoring (12.0 ± 6.5 glance/minute vs. 1.95 ± 0.65 glance/minute) and lane changing (8.4 ± 11.6 glance/minute vs. 0.36 ± 2.80 glance/minute) when visually distracted.

Similar to the following task, non-parametric analyses demonstrated significant changes caused by visual distraction in average off-road glance durations in passing when participants were monitoring (MS=273.23, p<0.001) or maneuvering (MS=273.23, p<0.001), and in 95th percentile glance durations during both monitoring (MS=258.66, p<0.001) and

maneuvering phases (MS=246.03, p<0.001). Average off-road glance duration was longer with the presence of visual distraction compared to without (0.43 ± 0.15 seconds vs. 0.26 ± 0.28 seconds for monitoring and 0.42 ± 0.17 seconds vs. 0.12 ± 0.12 seconds for maneuvering). Longer 95th percentile glance durations were also observed with the presence of visual distraction during monitoring phases (0.85 ± 0.35 seconds vs. 0.38 ± 0.74 seconds) and maneuvering phases (0.75 ± 0.31 seconds vs. 0.13 ± 0.14 seconds). Visual distraction also introduced significant changes in the percentage of off-road glances during monitoring (MS=286.03, p<0.001) and maneuvering phases (MS=246.03, p<0.001), as well as significant changes in the off-road glance frequency during monitoring (MS=280.02, p<0.001) and maneuvering phases (MS=234.66, p<0.001). Participants had longer off-road glance time when the visual distraction was present compared to absent (8.98% ± 4.9% vs. 0.33% ± 0.89% for monitoring and 6.48% ± 3.72% vs. 0.10% ± 0.35% for maneuvering). Off-road glance frequency increased with visual distraction (13.41 ± 7.93 glance/minute vs. 0.67 ± 1.52 glance/minute for monitoring and 10.12 ± 6.04 glance/minute vs. 0.48 ± 1.64 glance/minute for maneuvering).

The cognitive distraction only showed a significant influence on driver off-road glance percentage (MS=6.95, p=0.008) and off-road glance frequency (MS=8.79, p=0.003) in passing tasks during monitoring phases. Participants spent less time on off-road glances under cognitive distraction compared to none (3.84% ± 4.75% vs. 5.22% ± 6.14%), and made fewer off-road glances (5.62 ± 6.76 glance/minute vs. 8.09 ± 9.73 glance/minute).

5.4 Workload

An ANOVA on NASA-TLX scores revealed significant effects of the type of primary driving task ($F(1,133)= 4.03$, $p= 0.046$), visual distraction ($F(1,133)= 7.92$, $p= 0.006$), and cognitive distraction ($F(1,133)= 27.16$, $p<0.01$). Higher workload was associated with passing tasks compared to following tasks (61.87 ± 13.74 vs. 59.07 ± 13.55). Drivers perceived higher workload with the presence of visual distraction compared to none (62.85 ± 13.74 vs. 58.08 ± 13.27), and higher workload with the presence of cognitive distraction compared to none (65.77 ± 12.02 vs. 55.15 ± 13.21).

5.5 Correlation Analyses

5.5.1 Situation awareness and workload

Parametric correlation analyses were used to explore the interrelationship among levels of SA and workload for both following and passing tasks (see Table 5-7). In following tasks, the accuracy and response latency of Level 2 SA were positively related to the response latency of Level 1 SA ($r=0.23$, $p<0.001$ for Level 2 accuracy; $r=0.183$, $p<0.001$ for Level 2 latency). The latency of Level 2 SA was also positively related to the accuracy of Level 1 SA ($r=0.247$, $p<0.001$). The accuracy of level 3 SA was positively related to the accuracy of Level 1 SA ($r=0.09$, $p=0.048$), but negatively related to the response latency of Level 1 SA ($r=-0.150$, $p=0.001$). The latency of Level 3 SA was positively related to the latency of Level 1 SA ($r=0.29$, $p<0.001$) and accuracy of Level 2 SA ($r=0.103$, $p=0.025$), while negatively related to the accuracy of Level 1 SA ($r=-0.123$, $p=0.007$). In general, longer response times resulted in higher accuracy during operational driving control. More

accurate Level 1 SA led to a shorter response times to Level 3 SA probes. That is, correct perception of roadway states allowed drivers to more easily project future states. The correlations among the various response measures at the different levels of SA also supports Endsley (1995a) concept that each level builds on the prior level of complex system control. Workload was only negatively related to the accuracy and the latency of Level 3 SA ($r=-0.163$, $p<0.001$ for accuracy and $r=-0.154$, $p<0.001$).

In passing tasks, the reliance of higher level of SA on lower level of SA, and bonds between response latency and accuracy appeared stronger than for following tasks. This was in-line with expectation for the study. The latency of responses to Level 2 SA probes was positively related to the latency of responses to Level 1 probes ($r=0.383$, $p<0.001$) and the accuracy of Level 2 SA ($r=0.1412$, $p=0.003$). The accuracy of Level 3 SA was positively related to the accuracy of Level 1 ($r=0.257$, $p<0.001$) and Level 2 SA ($r=0.097$, $p=0.039$), as well as the latency of Level 1 ($r=0.225$, $p<0.001$) and 2 SA ($r=0.186$, $p<0.001$). The latency of Level 3 SA was positively related to the latency of both Level 1 ($r=0.25$, $p<0.001$) and Level 2 SA ($r=0.115$, $p=0.015$), and the accuracy of Level 2 ($r=0.465$, $p<0.001$) and 3 SA ($r=0.277$, $p<0.001$). Similar to operational control, higher accuracy was associated with longer response times to probes. Results also suggested that accurate Level 1 and 2 SA were the basis for accurate projection. However, the negative correlation between the accuracy of Level 2 SA and the accuracy of Level 1 SA ($r =- 0.151$, $p < 0.001$) suggested that drivers may still develop higher levels of SA even though they have insufficient lower level SA in tactical driving. Different than in the following task, workload was negatively related to the accuracy of Level 2 SA ($r=-0.163$, $p<0.001$) in passing instead of Level 3 SA.

It worth noting that although significant correlations were found among SA measures and workload, only two of the correlation coefficients were greater than 0.30; a rough psychological criterion for practical importance. These coefficients described the positive linear associations between the latency of Level 1 SA and Level 2 SA, and the latency of Level 2 and Level 3 SA during passing tasks (see Table 5-7).

Table 5-7. Correlations among levels of SA and workload

		Level 1 Latency	*Level 2 Accuracy*	*Level 2 Latency*	*Level 3 Accuracy*	*Level 3 Latency*	*Workload*
Following	**Level 1 Accuracy**	r=-0.063	r=-0.045	**r=0.247; p<0.001**	**r=0.09; p=0.048**	**r=-0.123 p=0.007**	r=0.090
	Level 1 Latency		**r=0.23; p<0.001**	**r=0.183; p<0.001**	**r=-0.150; p=0.001**	**r=0.29; p<0.001**	r=0.075
	Level 2 Accuracy			r=0.074	r=0.066	**r=0.103; p=0.025**	r=0.080
	Level 2 Latency				r=-0.088	r=0.332	r=-0.003
	Level 3 Accuracy					r=-0.047	**r=-0.163; p<0.001**
	Level 3 Latency						**r=-0.154; p<0.001**
Passing	**Level 1 Accuracy**	r=0.061	**r=-0.151; p=0.001**	r=0.1152	**r=0.257; p<0.001**	r=-0.023	**r=-0.105;**
	Level 1 Latency		r=-0.029	**r=0.383; p<0.001**	**r=0.225; p<0.001**	**r=0.25; p<0.001**	r=-0.041
	Level 2 Accuracy			**r=0.141, p=0.003**	**r=0.097; p=0.039**	**r=0.115; p=0.015**	**r=-0.163; p<0.001**
	Level 2 Latency				**r=0.186; p<0.001**	**r=0.465; p<0.001**	r=0.032
	Level 3 Accuracy					**r=0.277; p<0.001**	r=-0.057
	Level 3 Latency						r=0.065

Note: Correlation coefficients in bold are statistically significant. r represents the correlation coefficient derived from parametric correlation data analyses.

5.5.2 Eye-tracking measures and internal metrics

Because all the eye tracking measures did not confirm with the normal distribution, a Spearman's (ρ) non-parametric correlation analysis was conducted to explore the relationship between driver gaze pattern and driver SA. As shown in Table 5-8, there were many significant relationships between driver SA and gaze behavior. Especially when drivers performed monitoring in following tasks, almost all of the eye-tracking measures were related to the levels of SA, in terms of both accuracy and latency. As the complexity of maneuvers increased during lane changing, as compared to lead-car following, the relationship between eye-tracking measures and response latency to Level 2 and 3 SA probes became weak. In general more off-road glances related to longer response latency but higher accuracy in responding to SA probes. Frequent off-road glances were even correlated with shorter Level 3 SA during monitoring phases. Only average off-road glances were positively related to workload when drivers performed monitoring. However, all the correlation coefficients were small in magnitude (<0.3), except the positive correlation between off-road glance frequency and Level 3 SA accuracy. This suggested that higher level SA may direct driver attention allocation strategies under operational control.

Compared to following tasks, eye-tracking measures were only related to lower levels of SA, i.e., the accuracy and latency of Level 1 SA and the accuracy of Level 2 SA. Although more off-road glances and longer off-road glance durations still correlated with higher accuracy of Level 1 SA, off-road glance behavior led to degraded accuracy of Level 2 SA and shortened response times to the SA queries. Interestingly, the magnitude of all the

correlation coefficients between the eye-tracking measures and SA accuracy were greater than 0.3 for Level 2 SA during passing. Similarly, most of the coefficients between eye-tracking measures and Level 1 SA accuracy were greater than 0.3 in magnitude. This suggested that the relationship between SA and eye movements became stronger as drivers engaged in higher level driving control (i.e., tactical behavior). In distributing visual attention to distraction tasks, drivers might intentionally devote more resources to perceive the roadway environment but sacrifice accuracy of comprehension of surrounding traffic.

Workload was also related to gaze behavior when drivers performed passing tasks. Although the correlation coefficients were not large, all eye-tracking measures were significantly related to workload in passing lead vehicles. That is, more off-road glances were associated with higher perceptions of workload (see Table 5-8).

Table 5-8. Correlations among eye-tracking responses, SA and workload

			Level 1 Accuracy	***Level 1 Latency***	***Level 2 Accuracy***	***Level 2 Latency***	***Level 3 accuracy***	***Level 3 Latency***	***Workload***
Following	**Monitoring**	**Off-road glance frequency**	**ρ=0.167; p<0.001**	**ρ=0.177; p=<.001**	**ρ=0.094; p=0.039**	**ρ=0.135; p=0.003**	**ρ=0.318; p=<.001**	**ρ=-0.224; p=<.001**	ρ=0.0145;
		Average off-road glance duration	ρ=0.067;	**ρ=0.220; p=<.001**	**ρ=0.157; p=0.001**	**ρ=0.106; p=0.02**	**ρ=0.118; p=0.010**	**ρ=-0.282; p=<.001**	**ρ=0.128; p=0.005**
		percentage of off-road glances	**ρ=0.123; p=0.007**	**ρ=0.205; p=<.001**	**ρ=0.1167; p=0.011**	ρ=0.0582;	**ρ=0.261; p=<.001**	**ρ=-0.234; p=<.001**	ρ=0.0335;
		95 percentile off-road glances duration	**ρ=0.120; p=0.009**	**ρ=0.172; p<0.001**	**ρ=0.138; p=0.003**	**ρ=0.104; p=0.024**	**ρ=0.189; p=<.001**	**ρ=-0.277; p=<.001**	ρ=0.0803;
	Maneuvering	**Off-road glance frequency**	**ρ=0.126; p=0.006**	**ρ=0.112; p=0.014**	**ρ=0.1149; p=0.012**	ρ=0.069;	**ρ=0.215; p=<.001**	ρ=-0.081;	ρ=-0.0044;
		Average off-road glance duration	**ρ=0.128; p=0.005**	**ρ=0.136; p=0.003**	**ρ=0.14; p=0.002**	ρ=0.0176;	**ρ=0.182; p=<.001**	ρ=-0.0753;	ρ=0.0048;
		percentage of off-road glances	**ρ=0.113; p=0.013**	**ρ=0.129; p=0.005**	**ρ=0.135; p=0.003**	ρ=0.0407;	**ρ=0.180; p=<.001**	ρ=-0.0747;	ρ=-0.0018;
		95 percentile off-road glances duration	**ρ=0.116; p=0.011**	**ρ=0.133; p=0.004**	**ρ=0.135; p=0.003**	ρ=0.0409;	**ρ=0.176; p=0.001**	ρ=-0.0726;	ρ=0.0029;
Passing	**Monitoring**	**Off-road glance frequency**	**ρ=0.398; p<0.001**	ρ=-0.051;	**ρ=-0.481; p=<0.001**	**ρ=-0.4016; p=<.0001**	ρ=0.1348; p=0.0043	ρ=0.0194;	ρ=0.0995; p=0.0353
		Average off-road glance duration	ρ=0.238; p<0.001	ρ=-0.087; p=0.065	**ρ=-0.375; p<0.001**	ρ=0.0137;	ρ=0.0741;	ρ=-0.0525;	ρ=0.2339; p<.0001
		percentage of off-road glances	**ρ=0.369; p<0.001**	ρ=-0.070;	**ρ=-0.450; p<0.001**	ρ=0.0191;	ρ=0.1329; p=0.0048	ρ=0.0096;	ρ=0.1185; p=0.012
		95 percentile off-road glances duration	ρ=0.294; p<0.001	ρ=-0.075;	**ρ=-0.439; p=<0.001**	ρ=0.0251;	ρ=0.0856;	ρ=-0.0348;	ρ=0.1857; p<.0001

Table 5-8 Continued

			Level 1 Accuracy	*Level 1 Latency*	*Level 2 Accuracy*	*Level 2 Latency*	*Level 3 accuracy*	*Level 3 Latency*	*Workload*
Passing	**Maneuvering**	**Off-road glance frequency**	**ρ=0.416; p<0.001**	ρ=-0.152; p=0.001	**ρ=-0.455; p=<.001**	ρ=0.0135;	ρ=0.057;	ρ=-0.048;	ρ=0.138; p=0.003
		Average off-road glance duration	**ρ=0.340; p<0.001**	ρ=-0.167; p<0.001	**ρ=-0.378; p=<.001**	ρ=-0.031;	ρ=0.051;	ρ=-0.100; p=0.034	ρ=0.177; p<0.001
		percentage of off-road glances	**ρ=0.390; p<0.001**	ρ=-0.175; p<0.001	**ρ=-0.423; p=<.001**	ρ=-0.054;	ρ=0.057;	ρ=-0.051;	ρ=0.148; p=0.002
		95 percentile off-road glances duration	**ρ=0.360; p<0.001**	ρ=-0.194; p=<.001	**ρ=-0.402; p=<.001**	ρ=-0.041;	ρ=0.055;	ρ=-0.076;	ρ=0.166; p<0.001

Note: Correlation coefficients in bold are statistically significant. ρ represents the correlation coefficient derived from Spearman's non-parametric correlation analyses.

5.5.3 Driving performance and internal behavior measures

The correlations among driving performance, SA and workload are summarized in Table 5-9. Despite the fact that many significant correlations were observed, none of the coefficients indicated that one response served to explain greater than 30% of the variability in another response. Two inferences can be made on this basis: 1) SA does not solely determine the quality of driving performance; and 2) driver overt behavior is not sufficient to reflect all changes in driver SA or internal cognitive processes, which is consistent with the pervious study of real-time probe measures by Jones & Endsley (2004). However, such significant correlations should not be disregarded in attempting to explain driver behavior in different types of tasks.

In following tasks, higher variance in speed control may lead to lower accuracy of Level 1 (ρ =-0.170, p<0.001) and Level 3 SA (ρ =-0.139, p=0.002). Similarly, higher steering entropy during maneuvering (lane changing) was also negatively related to the accuracy of Level 1 SA (r=-0.158, p<0.001) and Level 3 SA (r=-0.104, p=0.023). However, larger steering entropy during monitoring phases was related to more accurate Level 2 SA (ρ =0.117, p=0.011). Larger headway distance was related to more accurate Level 1 SA (r= 0.107, p=0.019) and shorter latency of Level 1 (r=-0.101, p=0.029) and Level 3 SA (r=-0.110, p=0.017). Larger lane deviations may led to lower accuracy of Level 2 SA (r=-0.104, p=0.023) but shorter response times to Level 2 SA probes (r=-0.184, p<0.001). Interestingly, greater speed and longer lane changing times were related to shorter response latency of Level 2 SA (ρ =-0.098, p=0.033 for speed variance; r=-0.090, p=0.05 for completion time)

but the coefficients were extremely small. Only lane changing time was significantly correlated with workload albeit weakly (r=0.093, p=0.044).

When performing passing tasks, larger safety margins were associated with shorter latency of Level 1 SA (ρ =-0.145, p=0.002 for headway distance; ρ =-0.097, p=0.041 for time-to-collision; and r=-0.126, p=0.006 for headway time). Larger headway distance and longer headway time also correlated with shorter response latency of Level 2 SA (ρ =-0.113, p=0.017 for headway distance; and r=-0.142, p=0.002 for headway time). With respect to speed control, larger speed variance was associated with longer response latency of Level 2 (ρ =0.181, p<0.001) and Level 3 SA (ρ =0.156, p=0.001). Lower accuracy of Level 2 SA was related to higher steering entropy during both monitoring (r=-0.113, p=0.019) and maneuvering phases (r=0.098, p=0.044). Larger steering entropy during monitoring was related to shorter response latency of Level 1 SA (ρ =-0.108, p=0.022); while larger steering entropy during maneuvering was related to longer response latency of Level 2 SA (r=0.098, p=0.044). Longer passing time was associated with shorter response time to Level 1 SA queries. Opposite to following task performance, speed variance in passing was associated with changes in perceived workload. Drivers rated workload higher with larger speed variance (ρ =0.161, p<0.001).

Table 5-9. Correlations among driving performance, SA and workload

		Level 1 Accuracy	***Level 1 Latency***	***Level 2 Accuracy***	***Level 2 Latency***	***Level 3 Accuracy***	***Level 3 Latency***	***Workload***
Following	Speed variance	**ρ=-0.170; p<0.001**	ρ=0.041;	ρ=0.039;	**ρ=-0.098; p=0.033**	**ρ=-0.139; p=0.002**	ρ=0.044;	ρ=0.012;
	Speeding percentage	ρ=-0.027;	ρ=-0.023;	ρ=-0.013;	ρ=0.000;	ρ=-0.007;	ρ=0.002;	ρ=-0.037;
	Headway distance	ρ=0.067;	ρ=-0.060;	ρ=0.052;	ρ=0.034;	ρ=0.049;	ρ=-0.086;	ρ=0.042;
	Time to collision	ρ=0.017;	ρ=-0.021;	ρ=0.020;	ρ=-0.006;	ρ=0.015;	ρ=-0.064;	ρ=-0.002;
	Headway time	**r=0.107; p=0.017**	**r=-0.101; p=0.029**	r=0.055	r=0.032	0.086	**r=-0.110; p=0.017**	ρ=0.038;
	Lane deviation	r=-0.0639	r=-0.001	**r=-0.104; p=0.023**	**r=-0.184; p<0.001**	-0.061	r=-0.084	r=-0.020;
	Steering entropy during monitoring	ρ=-0.0752;	ρ=0.082;	**ρ=0.117; p=0.011**	ρ=0.051;	ρ=0.068;	ρ=-0.078;	r=-0.054;
	Steering entropy during maneuvering	**r=-0.158; p<0.001**	r=0.015	r=0.039	r=-0.016	**r=-0.103; p=0.023**	r=-0.067	r=0.018;
	Reaction time to the lead vehicle lane changing	r=0.0818	r=0.07	r=0.059	r=0.041	r=-0.001	r=0.019	r=0.089;
	Completion time of lane changing	**r=0.150; p=0.001**	r=0.002	r=-0.083	**r=-0.090; p=0.05**	r=0.053	r=-0.053;	**r=0.093; p=0.044**
Passing	Speed variance	ρ=0.024	ρ=-0.014	ρ=-0.066	**ρ=0.181; p<0.001**	ρ=0.039	**ρ=0.156; p=0.001**	**ρ=0.161; p<0.001**
	Speeding percentage	ρ=0.029	ρ=-0.034	ρ=0.009	ρ=-0.008	ρ=-0.001	ρ=0.015	ρ=-0.021;
	Headway distance	ρ=-0.049	**ρ=-0.145; p=0.002**	ρ=-0.042	**ρ=-0.113; p=0.017**	ρ=-0.022	ρ=-0.039	ρ=0.016;
	Time to collision	ρ=-0.034	**ρ=-0.097; p=0.041**	ρ=-0.003; p=0.954	ρ=-0.090;	ρ=-0.017	ρ=-0.033	ρ=0.020;

Table 5-9 Continued

		Level 1 Accuracy	***Level 1 Latency***	***Level 2 Accuracy***	***Level 2 Accuracy***	***Level 3 Accuracy***	***Level 3 Latency***	***Workload***
Passing	Headway time	r=-0.014	**r=-0.126; p=0.006**	r=-0.033	**r=-0.142; p=0.002**	r=-0.004	r=-0.079	ρ=0.039;
	Lane deviation	r=-0.048	r=0.072	r=-0.0725	r=0.0046	r=-0.092	r=-0.001	r=0.037;
	Steering entropy during monitoring	ρ=0.001;	**ρ=-0.108; p=0.022**	**ρ=-0.129; p=0.006**	ρ=0.037;	ρ=0.048;	ρ=-0.007;	r=0.038;
	Steering entropy during maneuvering	r=0.077	r=0.001	**r=-0.113; p=0.019**	**r=0.098; p=0.044**	r=0.090	r=-0.007	r=0.017;
	Reaction time to lead vehicle deceleration	ρ=0.048;	ρ=-0.056;	ρ=-0.057;	ρ=0.013;	ρ=0.034;	ρ=0.005;	r=0.027;
	Passing time	r=0.0279;	**r=-0.134; p=0.005**	r=-0.028;	r=-0.089;	r=0.037;	r=-0.085;	ρ=-0.003;

Note: Correlation coefficients in bold are statistically significant. r represents correlation coefficients derived from parametric correlation analyses; while ρ represents correlation coefficients derived from Spearman's non-parametric correlation analyses.

5.5.4 Summary of correlations analyses

The correlation analyses revealed valuable insights among SA measures and workload. In following tasks, the relationships among levels of SA revealed dependence of higher levels (comprehension and projection) on perception; but, the dependence was not strong. Compared to following tasks, the correlations among levels of SA were stronger in passing tasks. In addition, changes in perceived workload were only associated with changes in roadway state projection demands; whereas increases in perceived workload were also associated with lower accuracy of Level 1 and 2 SA in passing. This suggests SA measures representing different cognitive elements that are different from perceived workload measure.

As expected, measures of driver internal states were related to driver overt behaviors. Although weak but significant correlations were observed between eye-tracking measures and all levels of SA in following, strong correlations between gaze behavior and lower level of SA were only observed when tactical control was involved. This suggests that drivers may allocate visual attention to maintain accurate perception and comprehension only when required cognitive activities become challenging and require explicit awareness.

With respect to driving performance, although none of the correlations with the other types of response measures were considerably strong, significant correlations may still provide some insights into how performance influences driver SA and perceived workload. For example, larger variances in steering and speed control might lead to decreases in accuracy of SA. Tactical vehicle maneuvers, such as lane changing, may lead to increased workload as compared to when only operational driving control is required. Increases in

driver workload may also reflect degradations in basic driving control actions, such as speed variance, when operational control is required.

5.6 Discussion of Experiment Results

Based on the experiment result, the presence of both visual and cognitive distractions not only led to driver external behavior changes, but also affected drivers' internal understanding of the roadway environment. However, drivers' vulnerabilities to each type of distraction were mediated by level of driving control involved in concurrent driving tasks (see Table 5-10 and Table 5-11).

In line with expectations, visual distraction attracted focal vision and resulted in higher average off-road glance durations and more frequent off-road glances across levels of driving control as compared to normal driving conditions. Visual distraction increased driver perceived workload and was generally associated with higher speed deviations from posted limits (Engström et al., 2005; Victor, Harbluk, & Engström, 2005). However, since the visual distraction was designed to minimize cognitive load, it may not directly translate to a decrement in SA or driving performance, but rather it may trigger driver adaptation behaviors. For example, participants demonstrated enhanced perception of roadway conditions under visual distractions across levels of driving control. Because the following task mainly required operational control, and use of limited cognitive resource, adaptive behavior was more commonly observed when drivers performed following than passing. That is, participants maintained the same level of comprehension accuracy under visual distraction as when they drove normally; however, there was a comprise in response latency to Level 2 SA

probes. Drivers also showed higher accuracy in Level 3 SA and quicker responses to Level 3 SA probes than under normal driving conditions. Drivers may have felt the need to focus on projection of roadway states to compensate for reduced visual attention due to the distraction task. Relying on the greater SA, participants successfully maintained steering control under visual distraction like they did without distraction in the following task. Participants also reacted to lead vehicle lane changes more quickly under visual distraction in the following task, based on perceptions of task time pressure and concern for traffic avoidance. It is possible that drivers were aware of the possibility of becoming visually distracted from the driving task and consciously focused on performance in changing lanes.

In contrast, as the passing task involved tactical driving control and was more cognitively demanding than following, drivers did not (or could not) adapt their behavior to compensate for the visual distraction as much as they did in following. Compared to driving without distractions, they showed less accurate comprehension of the driving environment with the presence of visual distraction, which has been found to be critical for tactical control (Jin & Kaber, 2009; Matthews et al., 2001). As a consequence, participants took a longer time to react to lead vehicle deceleration and perform their passing maneuvers.

Cognitive distraction mainly competed for cognitive processing resources, as expected. This distraction was also associated with increased perception of workload as well as degraded Level 2 and 3 SA. Under cognitive distraction, drivers showed increased latency in Level 2 SA, as well as decreased accuracy of Level 3 SA across types of driving control. Similar to visual distraction, adaptive behaviors in response to cognitive distractions were also observed, especially during following tasks. The presence of cognitive distraction did

not result in changes in driver gaze behavior and steering control while monitoring lead car maneuvers. The times for drivers to complete a lane-change were longer and steering control actions were less frequent during lane changing under cognitive distraction, indicative of adaptation, as compared to the visual distraction and dual-distraction conditions. As a consequence of adaptation, participants showed improved accuracy of Level 1 SA, which was fundamental for operational control. As drivers devote more attention to perceiving roadway environment cues, they may become more confident in their driving and more ready to respond to environmental changes, as evidenced by a shorter time-to-collision and a shorter response time to lead vehicle lane changes.

However, when drivers performed passing under cognitive distraction, results were mixed. Participants showed reduced gaze dispersion (i.e., fewer off-road glances) (Victor et al., 2005) but increased speed variance. In addition to showing reduced steering control during maneuvering periods, they also produced fewer steering control actions under cognitive distraction during monitoring phases, as compared to the visual distraction and dual distraction conditions. As the passing task involved tactical control, the cognitive load appeared to be higher than for the following task. Consequently, drivers showed greater decrements in SA and performance with cognitive distraction, as compared to following tasks. In the presence of cognitive distraction, participants did not attempt to actively compensate for the increased load on attentional resources through driving behaviors and they exhibited greater response latency to both Level 2 and 3 SA probes, as well as degraded Level 3 SA accuracy.

These findings are also in line with previous research on operational tasks, which suggested that drivers may adapt to cognitive distractions and maintain driving safety by increasing their headway time (Strayer et al., 2003). However, such adaptation may fail when drivers are engaged in tactical control of a vehicle, wherein they adopt similar headway times as compared to without a distraction condition (Horrey & Simons, 2007). It is worth noting that the current study specifically instructed drivers to maintain their headway distance to the lead vehicles when performing both types of primary driving tasks. It is possible that the safety margin measures recorded in the present study may not have been sensitive enough to demonstrate driver adaptive behaviors. However, the SA and driving performance measures, including reaction time to lead vehicle actions as well as maneuver completion times in passing/lane-changing, did reveal driver adaptive behaviors.

In general, the simultaneous distraction condition led to the highest perceived workload and resulted in the worst driving performance among all driving conditions. Under simultaneous distractions driver exhibited the worst steering control as compared to all other conditions across levels of driving control. Even during the monitoring phases in following tasks, drivers produced greater steering entropy compared to the normal driving condition, while none of the single-modality distractions led to significant change in steering control. Participants demonstrated similar eye behaviors under simultaneous distraction as they showed when experiencing visual distractions. Similar to the results on single-modality distractions, the influences of simultaneous distraction on SA also depended on the control modes involved in the concurrent driving tasks. In following tasks, participants did not achieve higher perception accuracy. They took longer time to respond to Level 1 SA probes.

Although drivers may have realized the need to make greater projections of roadway states in the presence of visual distraction, they were not able to achieve higher Level 3 SA under simultaneous distractions. In the passing task, visual distraction and cognitive distraction acted in a simple additive manner; and fewer interactions were observed than in the following task (Yi-Ching Lee, J. D. Lee, et al., 2007). That is, drivers showed increased latency and degraded accuracy of Level 2 and 3 SA under simultaneous distraction. Drivers also attempted to maintain their perception of the roadway as they did when they experienced visual distraction.

In summary, if a driver has to manipulate an in-vehicle device, his/her tactical driving control may suffer to the extent of compromising safety, unlike with operational control. Decrements in driver SA may be a valuable indicator of the potential for safety issues when drivers are involved in tactical control as compared to when operational control is required. In addition, when distractions from both visual and cognitive modalities occur, driver adaptive behaviors may fail even under operational control. Mitigation strategies could be developed to address such a safety threat by warning drivers to disengage from secondary cognitive tasks when they are about to make tactical maneuvers (e.g., passing or turning at an intersection) and when the secondary tasks requiring multiple modalities of perception pose high workload demands.

Beyond the safety implication of distractions on driver behavior, the present study also supports the theory of explicit and implicit awareness (Bellet et al., 2009). One piece of evidence was driver adaptive behavior observed in following tasks when visual distraction was present. Operational control is primarily supported by implicit awareness and explicit

awareness is only expected to develop as emergencies occur or active task monitoring is required. In the following task, driver perception was required to monitor lead car actions. In the absence of visual distraction, drivers were able to keep their eyes on the road. Therefore, task information could occur based on driver implicit awareness. In contrast, when visual distractions were present, drivers realized that information in implicit awareness was not sufficient, because they could no longer maintain their gaze on the road. As uncertainty increased, drivers became more attentive to roadway conditions and used their explicit awareness to supplement for lost information during visual task time. That is, they attempted to maintain more task-related information in explicit awareness when visually distracted, as compared to none. As a result, they showed "equivalent" or "better" performance in answering SA queries when interacting with visual distraction tasks compared to none.

Another piece of evidence in support of Bellet's model for explaining the results of this study was based on the correlation analyses. As speculated in Section 1.3.2, real-time SA probes may represent the quality of explicit awareness, When the demands of explicit awareness were low, e.g., only operational driving control was required, the relation among levels of SA did not appear to be sequential in nature (i.e., Level 2 SA building on Level 1, etc.). The correlation coefficients among SA measures, although significant, did not reveal a strong dependence of higher-level SA on lower-level SA in following tasks. In contrast, in passing tasks, the latency of Level 2 SA was strongly correlated with the latency of Level 1 SA (r=0.383); the latency of Level 3 was strongly correlated with the latency of Level 2 SA. These coefficients indicated that when tactical control is required, drivers need explicit SA to support to address cognitive task demands, which may work in a sequential manner. Related

to this, workload was correlated with roadway state projection in the following task, when Level 3 SA was not necessarily required by concurrent driving tasks. However, workload was also correlated with Level 1 and Level 2 SA in passing tasks, which actually addressed concurrent driving task needs. It is possible that when the primary driving tasks were supported by implicit SA, some elements of the SA measure simply served as an indicator of workload. However, when explicit awareness was required, the SA measures directly reflected the changes in driver SA.

Table 5-10. Summary of experiment results on Situation Awareness and workload (NASA-TLX)

	Operational driving control			Tactical driving control		
	Visual	Cognitive	Both	Visual	Cognitive	Both
Level 1 SA	Improved accuracy	Improved accuracy	Longer latency, no decrease in accuracy	Increased accuracy	No degradation	Increased accuracy
Level 2 SA	Increased latency	Increased latency	[As good as no distraction]	**Degradation:** Decreased accuracy	**Degradation:** Increased latency;	**Degradation:** Increased latency; Decreased accuracy
Level 3 SA	Decreased latency, increased accuracy	Decreased accuracy	[As good as no distraction]	[As good as no distraction]	**Degradation:** Increased latency, Decreased accuracy[m]	**Degradation:** Increased latency, Decreased accuracy[m]
Workload	Increased	Increased	Increased	Increased	Increased	Increased

Note: * indicates that driver adaption strategies might have prevented degradations in performance and rendered levels of safety threat not applicable. [m] means marginally significant [p<0.1]; [As good as no distraction] means the effect of the experimental manipulation on the response was not different from the driver response in the absence of distraction.

Table 5-11. Summary of experiment results on driving performance and eye-tracking measures

		Operational driving control			Tactical driving control		
		Visual	Cognitive	Both	Visual	Cognitive	Both
Safety Margin		[As good as no distraction]	Leads to shorter TTC	Leads to shorter TTC	[As good as no distraction]	[As good as no distraction]	[As good as no distraction]
Speed Control		Leads to higher speed variance	[As good as no distraction]	Leads to higher speed variance	Leads to higher speed variance	Leads to higher speed variance	Leads to higher speed variance
Steering entropy	Monitoring	[As good as no distraction]	[As good as no distraction]	Larger	[Larger than cognitive only distraction condition]	[Smaller than visual only and dual distraction conditions]	Larger
	Maneuvering	[Larger than cognitive only distraction condition]	[Smaller than visual only and dual distraction conditions]	Larger	[Larger than cognitive only distraction condition]	[Smaller than visual only and dual distraction conditions]	Larger
Response time to the lead vehicle actions		Shorter	Shorter	Shorter	Longer	[As good as no distraction]	Longer
Task time (lane changing/passing)		[Shorter than cognitive only distraction conditions]	[Longer than visual only and dual distraction conditions]	[Shorter than cognitive only distraction conditions]	Longer	[As good as no distraction]	Longer
Off-road glances		Increased frequency and total time duration	[As good as no distraction]	Increased frequency and total time duration	Increased frequency and total time duration	Decreased frequency and total time duration	Increased frequency and total time duration
Glance duration		Increased	[As good as no distraction]	Increased	Increased	[As good as no distraction]	Increased

Note: * indicates that driver adaption strategies might have prevented degradations in performance and rendered levels of safety threat not applicable. [m] means marginal significant [p<0.1]; [As good as no distraction] means the effect of the experimental manipulation on the response was not different from the driver response in the absence of distraction.

CHAPTER 6 CLASSICIATION OF DISTRACTION STATES

6.1 Data Preparation

The data sets collected in the current research included various response measures with different scales. According to the literature review, scaling response measures to a common range [e.g., -1, 1] serves to assign equal numerical weight to each input in a classification methodology (see Eq. (6.1)). Some outliers were found in all eye-tracking measures, response times to SA queries, and two measures in vehicle control, including time-to-collision (TTC) and speed variance (SV). For example, the range for time-to-collision was between 2.3 and 778.5 seconds; however, 98% of time-to-collision responses were only 161.4 seconds, which was significantly smaller than the maximum value. Therefore, for response measures with such extreme ranges, the 98th percentile of those measures was used for scaling purposes, instead of using the maximum value (see Eq. (6.2)). In addition, because outliers appeared at the upper-end of the response ranges (i.e., greater than the 98th percentile values), all outliers were assigned a value of 1 (or -1) in the scaled data sets.

$$x' = -1 + \frac{x - \min x}{\max x - \min x} \times 2 \tag{6.1}$$

$$x' = -1 + \frac{x - \min x}{98\text{percentile } x - \min x} \times 2 \tag{6.2}$$

In addition, the statistical analyses may ensure that only variables revealing changes due to the experiment manipulations are included in models. This may also promote the efficiency of identifying distraction states. Therefore, SVMs models were built with only attributes or input variables that were significantly influenced by distractions as compared with SVMs including all attributes, especially for cognitive distractions. (All eye-tracking

measures that were used to fit classification models were significantly influenced by visual distraction.)

6.2 Visual Distraction Classification

6.2.1 SVM modeling for detecting visual distraction

The present study started with detection/classification of visual distraction state regardless of cognitive distraction. In line with expectation, visual distraction caused significant changes in driver gaze pattern for both following and passing tasks. Specifically, under visual distraction conditions, drivers exhibited greater off-road glances in terms of both duration and frequency. In spite of increased off-road glances, drivers may adapt to visual distraction when performing operational driving tasks by utilizing spare cognitive resources. Even in passing tasks, drivers may still maintain reasonably good Level 1 SA (perception) under visual distraction. Therefore, using internal behavior measures with performance measures for visual distraction state classification may not have additive value in terms of classification accuracy.

As suggested in Section 1.4.1, Fisher Linear Discriminant (FLD) analysis is a promising approach for classifying states of visual distraction. Unfortunately, the collected eye-tracking measures collected in the experiment violated the multivariate normality assumption and produced an unequal covariance matrix with respect to visual distraction. , Although the FLD method has shown robust performance when multivariate normality was slightly violated (Sever et al., 2005), FLD does assume equality of population covariance matrices. As a result, applying FLD to the eye-tracking measures to form a linear link with

visual distraction conditions was not considered an appropriate method for the current study. That said, linear discriminant analysis may still be a feasible approach for detecting states of driver visual distraction in similar research with larger data sets. Consequently, a distribution free learning algorithm, a SVM with 10 x 10-fold cross validation, was applied to identify visual distraction states by using eye-tracking measures. Related to this, drivers demonstrated consistent changes in gaze pattern under visual distraction in both following and passing tasks, even though there were significant differences in the magnitudes of eye measures among the primary task types. On this basis, application of SVMs to the responses collected across following and passing tasks was expected to yield similar classification performance as in fitting models to the data for following and passing independently.

6.2.2 Classification results for visual distraction

The classification procedures were conducted for following and passing tasks independently and jointly. The classification results are shown in Table 6-1. SVMs demonstrated high accuracy in visual distraction classification with eye-tracking measures only. The overall accuracy of SVMs for visual distraction classification when drivers were in operational or tactical control modes was generally above 95% with Cohen's κ greater than 0.95. Student *t*-tests were used to assess whether applying SVMs for distraction classification in following and passing tasks independently provided additional accuracy. Consistent with expectation, no significant differences were found between classification accuracies when using data across the driving task types and when only using data from one driving task or another.

Table 6-1. SVM model outputs for visual distraction classification with eye-tracking measures only

	Follow	***Passing***	***Overall***	***Follow vs. Overall***	***Passing vs. Overall***
Overall Accuracy	98.83%±2.64%	99.23%±2.55%	97.71%±1.65%	F(1,19)=1.14 p=0.27	F(1,19)=1.58 p=0.13
Cohen's κ	0.98	0.98	0.95		
Hit	94.78%±4.48%	97.12%±3.62%	95.91%±2.94%	F(1,19)=-0.67 p=0.51	F(1,19)=0.82 p=0.42
Correct Rejection	99.29%±1.69%	97.37%±3.50%	97.60%±2.34%	F(1,19)=1.85 p=0.08	F(1,19)=-0.2 p=0.86
Miss	5.22%±4.48%	2.88%±3.62%	4.09%±2.94%	F(1,19)=1.77 p=0.09	F(1,19)=0.35 p=0.73
False Alarm	0.71%±1.69%	2.63%±3.50%	2.40%±2.34%	F(1,19)=-3.15 p=0.01	F(1,19)=-1.0 p=0.33

Note: SDT measures ("hit", etc.) were previously defined in Section 3.3.

6.2.3 Sensitivity analysis of visual distraction

FSPP sensitivity analyses were conducted to assess the influence of each eye-tracking measure (i.e., gaze attribute) on the uncertainty of model outputs. As shown in Table 6-2, The FSPP of SVMs for classifying visual distraction across the two primary driving tasks ranged from 1.13% to 2.04%. Pair-wise *t*-tests suggested only off-road glances across driving segments while monitoring resulted in significantly smaller influence on estimated posterior probabilities of visual distraction compared to the 95th percentile of off-road glance duration during monitoring (F(1,19)=2.18, p=0.42) and the number of off-road glances in 1 minute (F(1,19)=2.20, p=0.40). However, these two significant differences were less than 1% in magnitude, which may not indicate any practical difference among eye-tracking measures in SVM output uncertainty. Similarly, the FSPP for sensitivity analyses on distraction classification in following tasks ranged between 0.74% to 1.38%, and 1.62% to 2.63% for passing tasks. No pair-wise comparisons of the influence of eye-tracking measures revealed statistically significant differences in FSPP for either of the primary tasks. Sensitivity

analyses were then applied to eye-tracking measures across the two task time segments, including monitoring and maneuvering. The corresponding FSPPs were consistent with those generated when evaluating the influence of measures for each of the time segments. That is, not only was the change in SVM output uncertainty small in magnitude (the maximum FSPP was 2.52%), but changes caused by any pair of measures were similar.

To further explore the influence of eye-tracking measures in output uncertainty, eye-tracking measures were grouped into two categories, including glance duration measures (i.e., average off-road glance duration and 95th percentile of off-road glance durations) and frequency measures (i.e., percentage of off-road glances across driving segments and the number of off-road glances in a 1-minute period). These measures were analyzed for each of the two task time segments, including monitoring and maneuvering. Frequency measures collected during monitoring segments showed the greatest FSPP among the groups of measures when analyzing both driving tasks independently or jointly. In addition, pair-wise *t*-tests showed significant differences between FSPPs for frequency measures during monitoring and other groups of measures (duration/frequency $\times$ monitoring/maneuvering) when fitting SVMs to either individual driving tasks or across driving tasks (all p-values were smaller than 0.001). However, no significant differences were found among the other three measurement groups. By removing frequency measures during monitoring, the output uncertainty of the SVM model changed by 5.29% $\pm$ 1.72% across the two driving tasks, by 4.59% $\pm$1.44% for the following task, and by 5.45% $\pm$ 1.97% for the passing task.

Table 6-2. Sensitivity analysis of eye-tracking measures in visual distraction classification.

		Overall		***Following***		***Passing***	
		FSPP	Rank	FSPP	Rank	FSPP	Rank
No Group: Individual measures							
Monitoring	Off-road glance per minute	1.88% ±1.00%	5	1.38% ±0.85%	1	2.43% ±1.43%	2
	Off-road glance percentage	1.91% ±1.06%	4	1.15% ±0.79%	3	2.40% ±1.21%	3
	Average glance duration	1.99% ±0.78%	3	1.27% ±0.76%	2	2.33% ±1.20%	4
	95th glance duration	1.13% ±0.39%	8	1.04% ±0.82%	5	2.63% ±1.25%	1
Maneuvering	Off-road glance per minute	2.02% ±1.21%	2	0.96% ±0.45%	6	2.23% ±1.48%	5
	Off-road glance percentage	1.70% ±0.98%	6	0.94% ±0.75%	7	1.65% ±0.86%	7
	Average glance duration	1.59% ±1.09%	7	0.74% ±0.83%	8	1.62% ±1.02%	8
	95th glance duration	2.04% ±1.26%	1	1.09% ±0.83%	4	1.77% ±1.00%	6
Group 1: By measurement category (off-road glance frequency and duration)							
Off-road glance per minute		2.52% ±1.45%	1	1.20% ±0.67%	2	1.92% ±0.73%	4
Off-road glance percentage		2.17% ±0.68%	2	0.98% ±0.83%	4	2.01% ±0.76%	3
Average glance duration		1.94% ±1.16%	4	1.24% ±0.56%	1	2.10% ±0.62%	2
95th glance duration		2.03% ±1.13%	3	1.04% ±0.92%	3	2.44% ±1.13%	1
Group 2: By segments (monitoring and maneuvering) and measurement category (off-road glance frequency and duration)							
Frequency measures in monitoring segments		5.29% ±1.72%	1	4.59% ±1.44%	1	5.45% ±1.97%	1
Duration measures in monitoring segments		1.86% ±0.71%	4	1.50% ±0.71%	2	2.45% ±1.11%	4
Frequency measures in maneuvering segments		2.17% ±1.00%	3	1.15% ±0.53%	4	3.26% ±1.19%	2
Duration measures in maneuvering segments		2.82% ±1.31%	2	1.19% ±0.61%	3	2.47% ±1.02%	3
Group 3: By segments (monitoring and maneuvering)							
Monitoring segments		22.9% ±2.55%	1	32.3% ±3.07%	1	9.36% ±1.55%	1
Maneuvering segments		4.13% ±0.88%	2	1.67% ±0.89%	2	7.60% ±2.65%	2

Additionally, all the eye-tracking measures were then analyzed according to the two time segments, i.e., monitoring and maneuvering. Results revealed that excluding measures

collected in monitoring segments led to a greater change in SVM output uncertainty than when removing measures recorded in maneuvering segments, especially for following tasks ($F(1,19) = 30.3$, $p<0.001$; 32.3% ± 3.07% vs. 1.67% ± 0.89%). However, there was no statistically significant difference in SVM output uncertainty when excluding eye-tracking measures collected in monitoring vs. maneuvering segments for passing.

6.3 Cognitive Distraction Classification

6.3.1 SVM modeling for cognitive distraction

Cognitive distraction affected every dimension of driver behavior in the experiment and its influence on any one dimension depended on the types of driving tasks. Because the influences of cognitive distraction were more complex compared to visual distraction, any one type of measure (internal behavior, overt behavior) may not be sufficient to classify cognitive distraction. For this reason, all response measures were included in SVM models for classifying cognitive distraction. In addition, cognitive distraction had greater influence on higher-level driver SA than visual distraction even in operational task performance. Accordingly, the inclusion of measures of driver internal behaviors in SVM models was expected to be significant. To assess such additive value of the various measures for distraction classification, SVMs with only external measures, including both eye-tracking and performance responses, were developed and compared with SVMs including all measures as inputs. Beyond these models, SVMs with only response measures that were significantly influenced by cognitive distraction were also constructed as a potential alternative to SVMs with all response measures. It was expected that such models might

produce comparable performance to full models. Similarly, SVMs with only external behavior measures that were significantly influenced by cognitive distractions were constructed as an alternative for SVMs with all external measures.

6.3.2 Results of cognitive distraction classification

Similar to the classification of states of driver visual distraction, SVM classifiers with 10 × 10-fold classification of cognitive distraction were applied to the following and passing task data sets independently and jointly. Ten estimations of model accuracy and prediction variance were collected on 10 replications of the process for a single type of SVM model. Subsequently, pair-wise comparisons were conducted to evaluate the differences between two types of SVM models. The SVM outputs are summarized in Table 6-3. Fitting SVM models according to different primary tasks showed advantages over fitting models across driving task types. There was a significant improvement in the prediction accuracy of SVM models for the following task with all response measures compared to models across task types ($F(1,19)=3.05$, $p=0.007$). (With respect to the denominator degrees of freedom in this test statistic, the total number of observations of prediction accuracy and variance was 2 types of models * 10 observations for each model = 20. Consequently, the error DOFs for each pair-wise comparison were 20 - 1 (for bias) = 19.) There was no significant difference in prediction accuracy of SVM models for the passing task with all response measures compared to models across task types. However, SVM models for the passing task with only response measures that were significantly influenced by cognitive distraction showed

superior classification accuracy as compared to models for the passing task including all response measures ($F(1,19)=2.11$, $p=0.049$).

Table 6-3. Prediction outputs of SVM models for classifying cognitive distraction

		Following	***Passing***	***Overall***
All Measures	Accuracy	96.06% ±3.49%	92.18% ±4.79%	91.76% ±2.79%
	Hit	94.84% ±4.72%	89.85% ±7.42%	91.40% ±4.00%
	Correct rejection	93.65% ±4.92%	90.78% ±6.36%	90.44% ±4.30%
	False alarm	6.35% ±4.92%	9.22% ±6.36%	9.56% ±4.30%
	Miss	5.16% ±4.72%	10.15% ±7.42%	8.60% ±4.00%
	Cohen's κ	0.92	0.84	0.84
External Measures Only	Accuracy	69.68% ±6.99%	57.70% ±3.24%	59.47% ±4.51%
	Hit	68.79% ±10.47%	58.15% ±12.57%	57.34% ±7.58%
	Correct rejection	68.17% ±9.65%	58.30% ±11.53%	60.59% ±8.43%
	False alarm	31.83% ±9.65%	41.70% ±11.53%	39.41% ±8.43%
	Miss	31.21% ±10.47%	41.85% ±12.57%	42.66% ±7.58%
	Cohen's κ	0.39	0.15	0.19
Measures were Significantly influenced by cognitive distraction	Accuracy	87.89% ±5.56%	95.05% ±4.07%	
	Hit	85.43% ±7.83%	93.51% ±6.27%	
	Correct rejection	87.15% ±7.26%	92.95% ±5.72%	
	False alarm	12.85% ±7.26%	7.05% ±5.72%	
	Miss	14.57% ±7.83%	6.49% ±6.27%	
	Cohen's κ	0.88	0.90	
External measures were significantly influenced by cognitive distraction only	Accuracy	48.40% ±7.23%	61.91% ±7.48%	
	Hit	63.18% ±18.11%	54.50% ±11.30%	
	Correct rejection	34.04% ±14.30%	67.09% ±10.84%	
	False alarm	65.96% ±14.30%	32.91% ±10.84%	
	Miss	36.82% ±18.11%	45.50% ±11.30%	
	Cohen's κ	0	0.24	

Note: Response measures that were significantly influenced by cognitive distraction in following tasks included time-to-collision, steering entropy during monitoring and maneuvering, accuracy of Level 1 SA, latency of Level 2 and 3 SA, and TLX workload scores. Response measures that were significantly influenced by cognitive distraction in passing tasks include speed variance, steering entropy during monitoring and maneuvering, number of off-road glances per minute, off-road glance percentage, accuracy and latency of Level 2 and 3 SA, and TLX workload scores.

In general, SVMs achieved high accuracy (greater than 90%) in classifying cognitive distraction with all response measures and with measures that were significantly influenced by cognitive distraction. In contrast, with only external measures, the prediction accuracy of models was only 69.68% for following and 57.70% for passing, on average. Cohen's κ

statistics also suggested weak agreement between the true distraction state and predictions of the classifier when using only external behavior measures as model inputs (0.39 for following and 0.15 for passing). Detailed comparisons between pairs of SVMs models are presented in Table 6-4. Based on the output for SVMs including all measures as inputs vs. only external measures, there was a significant improvement in classification accuracy by including internal process measures under all three analysis conditions, i.e., the following task only, the passing task only, and across the two primary tasks. The improvement in prediction accuracy was most substantial for the passing task at approximately 35%. Interestingly, reduced SVM models for passing, including as inputs only those measures that were significantly influenced by cognitive distraction, demonstrated equivalent or even slightly better prediction accuracy compared to SVMs with all measures (95.05% vs. 92.18%; $F(1,19)=1.44$; $p=0.17$). In cntrast, retaining only those measures that were significantly influenced by distractions in SVMs showed significantly degraded accuracy, as compared to models with all response measures, for the following task (87.89% vs. 96.06% ; $F(1,19)=3.94$; $p=0.001$).

Table 6-4. Comparison of SVMs for classifying cognitive distraction

	Following		***Passing***		***Overall***	
All response measures - External measures only						
Accuracy	26.38%	F(1,19)=10.7 p<0.001	34.48%	F(1,19)=18.87 p<0.001	32.29%	F(1,19)=19.25 p<0.001
Hit	26.05%	F(1,19)=7.17 p<0.001	31.70%	F(1,19)=6.87 p<0.001	34.06%	F(1,19)=12.57 p<0.001
Correct rejection	25.48%	F(1,19)=7.44 p<0.001	32.49%	F(1,19)=7.80 p<0.001	29.84%	F(1,19)=9.98 p<0.001
False alarm	-25.48%	F(1,19)=7.44 p<0.001	-32.49%	F(1,19)=7.80 p<0.001	-29.84%	F(1,19)=9.98 p<0.001
Miss	-26.05%	F(1,19)=7.17 p<0.001	-31.70%	F(1,19)=6.87 p<0.001	-34.06%	F(1,19)=12.57 p<0.001
All response measures- All measures significantly influenced by cognitive distraction						
Accuracy	8.17%	F(1,19)=3.94 p=0.001	-2.86%	F(1,19)=1.44 p=0.17		
Hit	9.41%	F(1,19)=3.26 p=0.004	-3.66%	F(1,19)=1.19 p=0.25		
Correct rejection	6.50%	F(1,19)=2.35 p=0.030	-2.16%	F(1,19)=0.80 p=0.43		
False alarm	-6.50%	F(1,19)=2.35 p=0.030	2.16%	F(1,19)=0.80 p=0.43		
Miss	-9.41%	F(1,19)=3.26 p=0.004	3.66%	F(1,19)=1.19 p=0.25		
All measures significantly influenced by cognitive distraction- External measures significantly influenced by cognitive distraction						
Accuracy	39.49%	F(1,19)=13.69 p<0.001	33.14%	F(1,19)=12.30 p<0.001		
Hit	22.25%	F(1,19)=3.57 p=0.002	39.01%	F(1,19)=9.54 p<0.001		
Correct rejection	53.11%	F(1,19)=10.5p <0.001	25.86%	F(1,19)=6.67 p<0.001		
False alarm	-53.11%	F(1,19)=10.5 p<0.001	-25.86%	F(1,19)=6.67 p<0.001		
Miss	-22.25%	F(1,19)=3.57 p=0.002	-39.01%	F(1,19)=9.54 p<0.001		
All external measures only - External measures significantly influenced by cognitive distraction						
Accuracy	21.28%	F(1,19)=6.69 p<0.001	-4.21%	F(1,19)=1.63 p=0.119		
Hit	5.61%	F(1,19)=0.85 p=0.407	3.65%	F(1,19)=0.68 p=0.503		
Correct rejection	34.13%	F(1,19)=6.26 p<0.001	-8.79%	F(1,19)=1.76 p=0.095		
False alarm	-34.13%	F(1,19)=6.26 p<0.001	8.79%	F(1,19)=1.76 p=0.095		
Miss	-5.61%	F(1,19)=0.85 p=0.407	-3.65%	F(1,19)=0.68 p=0.503		

6.3.3 Sensitivity analysis of cognitive distraction

FSPP sensitivity analyses were applied to SVM models with only measures that were significantly influenced by cognitive distraction to assess the influence of each attribute or response measure on the uncertainty of model outputs (see Table 6-5). For both tasks, internal measures, SA measures and TLX score, all showed considerable influence in output uncertainty with a minimum of 4.41%. In following tasks, the exclusion of any of the measures that were included in the SVMs model led to more than 10% change in estimated posterior probabilities of cognitive distraction. Among all the response measures, the TLX demonstrated the greatest influence on estimation uncertainty (FSPP=21.85%), followed by latency of Level 2 SA (FSPP=15.56%), latency of Level 3 SA (FSPP=15.24%) and accuracy of Level 1 SA (FSPP=14.28%). Similarly, for the passing task, the absence of the accuracy of Level 3 SA and TLX scores caused the estimated posterior probabilities of the model to change by more than 10%.

Interestingly, as perceived workload accounted for over 20% of the distraction state estimation uncertainty, it is possible that higher prediction accuracy may be due to driver perception of increased workload under cognitive distraction vs. actual changes in safety behavior or changes in SA. As opposed to following tasks, the influence of SA measures in prediction accuracy became the leading element in detecting cognitive distraction, especially the accuracy of Level 2 and 3 SA. This again serves as evidence of the increasing reliance of drivers on explicit awareness as the level of complexity of driving control increased.

Table 6-5. Sensitivity analysis of SVM models with only measures that were significantly influenced by cognitive distraction

Following			***Passing***		
Measure	FSPP	Rank	Measure	FSPP	Rank
Time to collision	10.64%±2.79%	7	Speed variance	6.53%±1.89%	5
Steering entropy in monitoring	11.94%±3.20%	6	Steering entropy in monitoring	5.20%±1.70%	8
Steering entropy in maneuvering	12.43%±1.94%	5	Steering entropy in maneuvering	6.51%±2.16%	6
Accuracy of Level 1 SA	14.28%±3.05%	4	# of off-road glance per minute in monitoring	5.03%±2.93%	9
Latency of Level 2 SA	15.65%±2.79%	2	Off-road glance percentage in monitoring	4.71%±3.54%	11
Latency of Level 3 SA	15.24%±2.46%	3	# of off-road glance per minute in maneuvering	4.97%±2.51%	10
TLX	21.85%±3.17%	1	Off-road glance percentage in maneuvering	4.41%±2.20%	12
			Latency of Level 2 SA	5.58%±1.98%	7
			Accuracy of Level 2 SA	10.83%±3.26%	2
			Latency of Level 3 SA	7.49%±1.83%	4
			Accuracy of Level 3 SA	12.01%±2.82%	1
			TLX	10.18%±2.15%	3

6.4 Integrated Classification of Visual and Cognitive Distraction

6.4.1 Classification strategies for detecting visual and cognitive distraction

As confirmed by the experiment results, visual distraction dominated the changes in driver visual behavior. Classification of visual distraction based on eye-tracking measures also showed satisfactory results. Therefore, one feasible approach was to classify visual distraction first using only eye-tracking measures, followed by cognitive distraction classification using SVM models including all response measures. However, experiment

results also revealed a significant interaction of visual and cognitive distraction on driving behavior and SA. The dual-distraction condition demonstrated unique behavior outcomes as compared to when drivers were influenced by visual or cognitive distraction, especially in following tasks. Hence, another feasible approach was to utilize a multi-category SVM approach to classify driver distraction states into four categories directly, including no distraction, visual distraction only, cognitive distraction only, and simultaneous distraction. This study applied both approaches to classify visual and cognitive distraction, simultaneously. The prior one was called the "two-step" distraction classification approach; the latter one was called the "direct mapping" distraction classification approach.

6.4.2 Results of "two-step" distraction classification approach

The first step of the "two-step" approach was to classify visual distraction by using SVMs with only eye-tracking measures. In this step, the dual-distraction condition was classified as visual distraction. The second step was to use any remaining cases/observations, which had not been classified as a visual distraction state, to detect the presence of cognitive distraction. The "two-step" approach was applied to collected data entries regardless of primary task types or according to the driving task types.

The SVM model outputs are summarized in Table 6-6. The "two step approach" demonstrated high accuracy (greater than 94%) in classifying both visual and cognitive distraction under all three classification settings. Comparison between SVM models fit to data on one primary task vs. both driving task types revealed few significant differences. SVMs for the following task had significant lower false alarm rates for all distractions as

compared to SVMs across driving task types (F(1,19)=2.12, p=0.047; 10.63% ± 12.24% vs. 24.75% ± 17.14%) as well as significantly lower false alarm rates for visual distraction (F(1,19)=2.20, p=0.040; 1.38% ± 3.56% vs. 9.63% ± 11.30%). SVMs for the passing task showed marginally significant lower miss rates for all distractions as compared to SVMs across driving task types (F(1,19)=2.03, p=0.056; 2.33% ± 2.67% vs. 5.17% ± 3.98%). High values and large variances were observed in estimated false alarm rates for cognitive distraction and overall distraction for all three SVM models (false alarm rates were all greater than 8%; and the variances were all greater than 10%). This probably resulted from fewer observations being used to train the SVMs in the simultaneous distraction analysis in detecting cognitive distraction.

Table 6-6. Results of the two-step approach to classification of visual and cognitive distraction

	Following	***Passing***	***Overall***
Hit - Visual distraction only	95.01% ±4.38%	97.22% ±3.37%	96.01% ±2.64%
Hit - Dual-distraction only	97.68% ±4.86%	97.00% ±4.98%	97.35% ±3.13%
Hit - Visual distraction in total	92.63% ±8.06%	97.57% ±4.33%	94.65% ±4.23%
Miss - Visual distraction in total	0.17% ±0.42%	1.04% ±2.03%	1.15% ±1.42%
Miss - Dual-distraction	0	1.52% ±3.49%	1.82% ±2.71%
False alarm - Visual distraction	1.00% ±2.55%	2.57% ±3.39%	2.53% ±2.30%
Correct rejection - Visual distraction	99.00% ±2.55%	97.43% ±3.39%	97.47% ±2.30%
Miss classify cognitive as visual distraction	0.96% ±2.71%	1.37% ±3.75%	1.85% ±2.67%
Hit - Cognitive distraction for the reduced set	93.41% ±7.34%	93.69% ±7.00%	92.54% ±6.09%
Miss - Cognitive distraction for the reduced set	6.59% ±7.34%	6.31% ±7.00%	7.46% ±6.09%
Hit - Dual as cognitive distraction for the reduced set	7.07% ±8.65%	7.30% ±8.10%	8.02% ±6.82%
False alarm - Any distraction	10.63% ±12.24%	13.50% ±13.83%	24.75% ±17.14%
False alarm as visual distractions	1.38% ±3.56%	5.50% ±7.94%	9.63% ±11.30%
False alarm as cognitive distractions	9.25% ±11.38%	8.00% ±10.80%	15.13% ±13.35%
Miss – Any distraction	2.33% ±2.67%	2.19% ±2.33%	5.17% ±3.98%
Total accuracy	94.38% ±3.62%	94.38% ±3.62%	94.20% ±2.39%
Cohen's kappa	0.83	0.92	0.91

6.4.3 Direct mapping distraction classification result

The "direct mapping" approach used the default multiple-category SVM strategy provided in R-language package e1071, i.e., the "one-against-one" approach (Chang & Lin, 2007). In the "one-against-one" approach, k*(k-1)/2 classifiers are constructed for data belonging to k classes, where each one is trained on data from two classes. Each data entry is classified as one-out-of-two potential states by one classifier. The final prediction of a data entry is given by a "max wins" strategy, which assigns any data entry to the state that received the maximum number of votes among all the k*(k-1)/2 classifiers. Previous research using such an approach produced robust classification results (Hsu & Lin, 2002). Similar to the "two-step" distraction classification approach, this "direct mapping" approach was also applied to following and passing tasks independently and jointly.

As shown in Table 6-7, the direct mapping multi-category SVMs also demonstrated high prediction accuracy (above 90% for the total accuracy) under all three classification settings. SVMs for the following task showed significant differences from SVMs for both driving task types in terms of hit rate in the dual-distraction condition ($F(1,19)=3.33$, $p<0.001$) and overall accuracy ($F(1,19)=2.22$, $p=0.04$). The hit rate for the dual-distraction condition and the overall accuracy were significantly higher for SVMs for the following task as compared with SVMs developed for predicting distraction state in both driving tasks, (97.68% ± 4.67% vs. 88.84% ± 6.98% and 94.20% ± 3.37% vs. 91.03% ± 2.99% respectively). No significant differences were observed between SVMs for the passing task only and SVMs across all driving task types.

Table 6-7. Results of the direct mapping approach to classification of visual and cognitive distraction

	Following	*Passing*	*Overall*
Hit - Visual distraction only condition	92.90% ±7.37%	88.12% ±9.35%	87.98% ±7.70%
Hit - Cognitive distraction only condition	91.04% ±9.34%	93.69% ±7.22%	92.38% ±5.09%
Hit - Dual-distraction condition	97.68% ±4.67%	81.26% ±11.4%	88.84% ±6.98%
False alarm - Visual distraction	0.13% ±0.40%	1.15% ±2.37%	0.22% ±0.64%
False alarm - Cognitive distraction	1.92% ±2.84%	0.56% ±1.28%	1.47% ±1.88%
False alarm - Any distraction	4.88% ±6.07%	3.14% ±5.22%	4.93% ±4.37%
Miss - Any distraction	2.76% ±3.09%	1.58% ±2.31%	2.66% ±1.87%
Correct rejection - Visual distraction	97.78% ±2.95%	97.60% ±3.47%	97.57% ±2.31%
Correct rejection – Any distraction	95.12% ±6.07%	96.86% ±5.22%	95.07% ±4.37%
Total accuracy	94.20% ±3.37%	90.13% ±4.01%	91.03% ±2.99%
Cohen's kapa	0.93	0.87	0.88

6.4.4 "Two-step" versus "direct mapping" distraction classification approaches

The "two-step" and "direct mapping" approaches were compared by applying *t*-tests to all analogous evaluation results generated with these two approaches. As shown in Table 6-8, for SVMs for the passing task, the "two-step" distraction classification approach showed a significantly higher hit rate for the visual distraction only condition, a significantly higher hit rate for the dual-distraction condition and a significantly higher overall classification accuracy. Similarly, for SVMs across driving task types, the "two-step" distraction classification approach also showed a significantly higher hit rate for the visual distraction only condition, a significantly higher hit rate for the dual-distraction condition and a significantly higher overall classification accuracy. However, the "two-step" approach to SVMs for the passing task and across tasks produced significantly higher false alarm rates for any distraction type. No significant difference was observed between the "two-step" and the "direct-mapping" approaches for following tasks. It is possible that including other response measures when classifying visual distraction actually reduces the likelihood of correct

classifications, especially when the behavioral outcomes of introducing cognitive and visual direction are similar. In the following task, such phenomenon was only observed in terms of response time to lead vehicle maneuvers. The presence of both distractions appeared to motivate drivers to take quick action. Related to this, reaction time was not included in the SVM classification process. In contrast, visual and cognitive distraction affected several aspects of driver performance in similar ways. For example, in passing tasks, both visual and cognitive distraction led to greater speed variances and degradation in Level 2 SA. Therefore, the "direct-mapping" approach was worse in predicting visual distraction states than the "two-step" approach. However, since "direct-mapping" used more data entries to train the SVM models for classifying cognitive distraction as well as all other states, the approach produced lower false alarm rates for the cognitive and dual-distraction condition than the "two-step" approach.

Table 6-8. Comparisons between the "Two-step" and "Direct-mapping" approaches.

	Following		***Passing***		***Overall***	
Comparison	Diff	T-test	Diff	T-test	Diff	T-test
Total accuracy	0.18%	F(1,19)=0.1 p=0.908	4.86%	**F(1,19)=2.9 p=0.01**	3.17%	**F(1,19)=2.6 p=0.017**
Hit dual distraction	0.01%	F(1,19)=0.0 p=0.998	15.8%	**F(1,19)=4.0 p=0.001**	8.51%	**F(1,19)=3.5 p=0.002**
Hit visual distraction only	2.11%	F(1,19)=1.1 p=0.31	9.10%	**F(1,19)=3.8 p=0.001**	8.03%	**F(1,19)=4.4 p<0.001**
Hit visual distraction (Total)	-2.6%	F(1,19)=-1.2 p=0.23	12.7%	**F(1,19)=4.8 p<0.001**	6.29%	**F(1,19)=3.3 p=0.004**
Hit cognitive distraction only	2.37%	F(1,19)=0.8 p=0.450	0	F(1,19)=0 p=1	0.15%	F(1,19)=0.1 p=0.934
False alarm (Total)	5.74%	F(1,19)=1.7 p=0.102	10.4%	**F(1,19)=3.4 p=0.003**	19.8%	**F(1,19)=7.7 P<0.001**
Miss distraction (Total)	-0.43%	F(1,19)=-0.1 p=0.91	0.61%	F(1,19)=0.2 p=0.863	2.51%	F(1,19)=0.6 p=0.563
Correct rejection (Total)	-5.74%	F(1,19)=-1.3 p=0.200	-10.4%	**F(1,19)= -2 p=0.04**	-19.8%	**F(1,19)=-3.5 p=0.002**

6.5 Discussion of Distraction Classification

In summary, the SVM classifiers achieved satisfactory performance in identifying visual distraction and cognitive distraction when drivers were performing both operational and tactical driving tasks. Regardless of the presence of cognitive distraction, eye-tracking measures proved to be a sufficient basis for classifying visual distraction. Separating following and passing tasks in the SVM modeling did not reveal an improvement in classification performance. In contrast, classifying cognitive distraction required the use of all types of response measures, especially those reflecting driver internal behaviors (SA and workload). Consequently, any driver (cognitive) distraction alerting system utilizing SA and workload measures may produce better performance than a system only relying on external behavior measures (Victor, 2005). In addition, separate SVM models for following and passing tasks have shown better performance, as compared to SVM models applied to combined data sets for both types of driving tasks. Interestingly, including only responses that were significantly influenced by distraction substantially improved the performance of the SVM models for the following task.

Two approaches were developed to classify visual and cognitive distractions simultaneously, including a “two-step” approach and a “direct-mapping” approach. Similar to the classification of cognitive distraction states, separate models for following and passing tasks showed prediction accuracy advantages over models applied to data on both types of driving tasks for both approaches. Additionally, for the following task, although the “two-step” approach showed superior performance in overall accuracy and hit rates for visual distraction, this approach also produced more false alarms as compared to the “direct-

mapping" approach. It is possible that driver alerting systems having low reliability could cause adverse behavior consequences (Maltz & Shinar, 2007). However, testing of the reliability of warning systems was beyond the scope of this study. Future research is needed to assess whether any decrements in driver behavior due to increased false alarms of the "two-step" distraction state classification approach would outweigh the potential advantage in classification accuracy as compared to the "direct mapping" approach. That is, additional work is needed to provide a sufficient basis to recommend one approach over the other.

CHAPTER 7 CONCLUSION

Based on multiple resource theory, the current study identified characteristics of visual and cognitive distraction tasks with unique influences on driver cognitive processes (Angell et al., 2006; Wickens, 2002, 2008). Visual distractions should attract focal vision and require manual responses, while the cognitive distractions should compete for cognitive resources by using spatial information coding and requiring verbal responses. These characteristics provide reference for similar research to evaluate driver behavior and performance in the presence of distractions. According to these characteristics, two distraction tasks were designed to uniquely represent the two distraction modalities in the current research.

An experiment was conducted on the influence of different modalities of distraction on driving behavior at the operational and tactical levels of control, by implementing two types of driving tasks, including following and passing. Both overt behavior measures and internal process indicators were collected during experiment trials. Drivers were affected by both distraction modalities and behavior outcomes were mediated by the control modes required by concurrent driving tasks. In general, driver vulnerability to both types of distraction were greater for passing tasks requiring tactical control, as compared to following tasks which only required operational control. Results suggested that drivers may benefit from mitigation technologies that provide warnings of the need to disengage from cognitively distracting tasks when were performing tactical driving maneuvers (e.g., turning at an intersection or passing). Furthermore, drivers generally need to avoid high demand secondary tasks requiring multiple perceptual modalities when they are driving.

As expected, the real-time SA probe technique provided valuable information for assessing driver internal processes. The SA response measures derived from this technique reflected the influence of the distraction tasks. In general, greater degradation of high-level SA was observed as the complexity of driving control increased. These internal changes were closely related to external behavior changes, particularly when drivers were engaged in tactical driving control. Related to this, the present research suggests the validity of real-time probes for assessing explicit awareness according to Bellet's model. When the presence of a distraction caused the emergence of explicit awareness under operational control, the probe technique reflected an improvement in the accuracy of driver SA. On the other hand, when a task largely relied on explicit SA, the probe measures revealed degradations in driver SA due to distractions. In addition, the SA measures showed different outcomes for when the formulation of explicit awareness was impeded by different distraction modalities. An example can be found in the results for comprehension probes during passing tasks. Driver comprehension was found to be the most important aspect of SA in tactical driving. Visual distraction caused degradations in Level 2 SA accuracy, and cognitive distraction led to degradations in Level 2 SA latency. Opposite to this, the workload measure (NASA-TLX score) showed both visual and cognitive distraction to result in a similar pattern of increases in perceived workload across the two types of driving tasks; only the response magnitude differed. This provides additional evidence that the real-time probe measure sensitively reflects changes in driver explicit awareness rather than workload or other internal processes.

Beyond supporting the validity of SA measures, this study also contributed to the prevalent SA theories (Bellet et al., 2009; Endsley, 1988). There is evidence that routine

tasks that drivers are familiar with, such as following tasks, are supported by implicit awareness (see Section 5.6). If cognitive demands remain low, the explicit aspect of SA may not develop in a sequential manner according to Endsley's model, in which the quality of a higher level of SA is dependent on the quality of a lower level of SA. As the need for explicit SA increases, the dependence of high level SA on low level SA also increases. In summary, Endsley's three-step model may truly describe the mechanism of explicit SA formulation, but not the overall structure of SA. The utilization of implicit or explicit awareness depends on the cognitive needs of required tasks, which depend on both task complexity and operator familiarity with the task. Knowledge of driver SA also appears to benefit the classification of driver distraction states, as discussed below.

Both visual and cognitive distraction states of drivers were effectively classified using SVM techniques. Accurate classification of visual distraction was made based on eye-tracking measures. However, classification of cognitive distraction required more information beyond the external behavior measures. In general, the efficiency of the distraction classification algorithms was substantially improved with SA measures, as compared to the results of prior research (Liang, 2009). Especially with higher levels of driving control, the driver SA changes measured by real-time SA probe measures in the passing task showed more significant influence in estimation uncertainty than other internal process indexes, e.g., the perceived workload (see Section 6.3.3). Beyond this, the current study also identified internal and external measures of driver behavior that were significantly influenced by distractions and used these measures as inputs to SVM models to improve classification performance, especially for passing tasks.

Two approaches were developed to accomplish integrated classification of driver visual and cognitive distraction, including: 1) a “two-step” approach for visual distraction classification based on eye-tracking measures, followed by detection of cognitive distraction based on any remaining cases which were not classified as visual distraction; and 2) a “direct-mapping” approach for classifying four distraction states by using a multi-category SVM strategy. Both approaches showed high accuracy in classifying distraction states; however, neither of them showed absolute superior performance over the other. Although the “two-step” approach showed a higher accuracy in detecting visual distraction, it produced more false alarms than the “direct-mapping” approach. Unfortunately, previous research on behavior consequences of false alarms in in-vehicle driver alerting/warning systems is not adequate for making a conclusion in favor of one of the two approaches. Therefore, additional investigations are needed to assess the comparative utility of these two classification algorithms.

In summary, the present research demonstrated the value of an internal process index for driver distraction state classification and developed two potential approaches for detecting cognitive and visual distraction simultaneously. Future distraction mitigation technology may require both SA and workload measures for distraction state classification. The classification approaches developed in this study could also be used to demonstrate or evaluate whether a new in-vehicle device might cause safety-critical visual or cognitive distraction states. Such a testing process might be enforced by Federal and state regulations, e.g., Department of Transportation, as required pre-screening for new in-vehicle technologies.

Technologies that can monitor driver cognitive and visual distraction states in real-time may also facilitate companies in selecting among alternatives for new in-vehicle devices, demonstrate or compare the potential distraction level associated with new designs, and identify critical steps in driver-device interaction that result in increased distraction.

The present study also aids the development of distraction mitigation strategies. For example, although visual distraction may be easily identified by using eye-tracking technology, the threshold for distraction warning may need to be adjusted according to the cognitive needs of the current driving task. That is, even though a visual distraction is detected, drivers may not receive warning until the duration of consecutive off-road glances exceeds a large threshold (e.g. greater than 1.8s when driving on a straight interstate highway; Wierwille, 1993). On the other hand, the impairment of high-level explicit SA, i.e., comprehension and projection, was observed when tactical driving was also required. As a result, mitigation technology may provide drivers with additional information on the roadway, such as safety margin information, beyond asking drivers to divert their attention to the roadway.

Beyond limited comparative assessments of the classification algorithms, another limitation of this research was the test driver population. Only younger drivers were recruited for the study, as they are considered by some state legislatures (e.g., North Carolina) to be particularly vulnerable to distraction while driving due to in-vehicle technologies or devices. Older drivers (65 yrs old or above) may show different behavior changes when they interact with distraction tasks (Chaparro & Alton, 2000; McPhee, Scialfa, Dennis, Ho, & Caird, 2004; Merat, Anttila, & Luoma, 2005). On one hand, although older drivers may be equally or

more susceptible to distractions than young drivers when interacting with in-vehicle devices, they are aware of their cognitive limitations and tend to compensate by changing their driving behavior based on experience (Zhang et al., 2009). Therefore, they may be less likely to have a distraction-related accident. On the other hand, when a distraction task becomes intense, decrements in perceptual and cognitive abilities of older drivers may outweigh the potential adaptation based on driver experience. This losing tradeoff may compound the influence of distraction tasks on performance, SA and perceived workload. Hence, there is a need to extend the current study to a broader range of the driver population.

In addition, the present study only investigate distractions in a discrete manner, e.g., a driver was visual distracted or not. It may serve as a initial step to demonstrate the implication of distraction at various aspects of driving behavior. Future research may evaluate driving behavior changed due to distractions at various level and identify the thresholds for the occurrences of visual and cognitive distraction under common driver circumstances. Finally, future research may also advance the present findings by developing methods to measure visual and cognitive demands of in-vehicle devices, and quantitatively relate such demands to driver behaviors.

REFERENCES

Angell, L. S. (2010). Conceptualizing effects of secondary task demands on event detection during driving: Surrogate method and issues. In G. L. Rupp (Ed.), *Performance metrics for assessing driver distraction: the quest for improved road safety* (pp. 42-72). Warrendale, Pennsylvania: SAE International. doi:10.4271/R402

Angell, L. S., Auflick, J., Austria, P. A., Kochhar, D. S., Tijerina, L., Biever, W. J., Diptiman, T., et al. (2006). *Driver Workload Metrics Project Task 2 Final Report*. *Security*. Washington, D.C.

Arora, S., Bhattacharjee, D., Nasipuri, M., Malik, L., Kundu, M., & Basu, D. K. (2010). Performance Comparison of SVM and ANN for Handwritten Devnagari Character Recognition. *Journal of Computer Science*, *7*(3).

Bedny, G., & Meister, D. (1999). Theory of Activity and Situation Awareness. *International Journal of Cognitive Ergonomics*, *3*(1), 63-72. doi:10.1207/s15327566ijce0301_5

Bellet, T., Bailly, B., Mayenobe, P., & Banet, A. (2009). A theoretical and methodological framework for studying and modelling drivers' mental representations. *Safety Science*, *47*(9), 1205-1221. Elsevier Ltd. doi:10.1016/j.ssci.2009.03.014

Bellet, T., Bailly, B., Mayenobe, P., & Georgeon, O. (2007). Cognitive modelling and computaional simulation. In C. Cacciabue (Ed.), *Modelling driver behaviour in automotive environments: critical issues in driver interactions with intelligent transport systems* (pp. 315-343). London: Springer.

Blanco, M., Biever, W. J., Gallagher, J. P., & Dingus, T. A. (2006). The impact of secondary task cognitive processing demand on driving performance. *Accident; analysis and prevention*, *38*(5), 895-906. doi:10.1016/j.aap.2006.02.015

Boles, D. B., Bursk, J. H., Phillips, J. B., & Perdelwitz, J. R. (2007). Predicting dual-task performance with the Multiple Resources Questionnaire (MRQ). *Human factors*, *49*(1), 32-45. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/17315841

Bolstad, C. A., Cuevas, H., Wang-Costello, J., Endsley, M. R., & Angell, L. S. (2010). Measurement of situation awareness for automobile technologies of the future. In G. Rupp (Ed.), *Performance metrics for assessing driver distraction: the quest for improved road safety* (pp. 195-213). Warrendale, Pennsylvania: SAE International. doi:10.4271/R-402

Bouckaert, R. R., & Frank, E. (2004). Evaluating the Replicability of Significance Tests for Comparing Learning Algorithms. In C. E. Brodley (Ed.), *Machine Learning, Proceedings of the Twenty-first International Conference*. Banff, Canada: AAAI Press. doi:10.1145/1015330.1015338

Boyraz, P., Sathyanarayana, A., & Hansen, J. (2010). Lane keeping performance metrics for assessment of audiotroy-cognitive distraction. In G. L. Rupp (Ed.), *Performance metrics for assessing driver distraction: the quest for improved road safety* (pp. 167-188). Warrendale, Pennsylvania: SAE International. doi:10.4271/R-402

Chang, C.-chung, & Lin, C.-jen. (2007). LIBSVM : a Library for Support Vector Machines. *Computer*, 1-26.

Chaparro, A., & Alton, J. (2000). Age related differences in driving performance and target identification. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting (44th)* (Vol. 44, pp. 56-59). San Diego, CA: Human Factors and Ergonomics Society.

Chen, C.-L., Kaber, D. B., & Dempsey, P. G. (2000). A new approach to applying feedforward neural networks to the prediction of musculoskeletal disorder risk. *Applied ergonomics*, *31*(3), 269-82. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/10855450

Chen, C.-L., Kaber, D. B., & Dempsey, P. G. (2004). Using feedforward neural networks and forward selection of input variables for an ergonomics data classification problem. *Human Factors and Ergonomics in Manufacturing*, *14*(1), 31-49. doi:10.1002/hfm.10052

Cherkassky, V. S. (2007). *Learning from data: Concepts, theory and methods*. (V. S. Cherkassky & F. M. Mulier, Eds.) (2nd ed.). Hoboken, NJ: IEEE press & Wiley-Interscinece.

Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurements*, (20), 37-46.

Cortes, C., & Vapnik, V. N. (1995). Support-vector networks. *Machine Learning*, (20), 273-297.

Dimitriadou, E., Hornik, K., Leisch, F., Meyer, D., Weingessel, A., & Friedrichleischr-projectorg, M. F. L. (2011). Misc functions of the department of statistics (e1071), TU Wien. Retrieved from http://cran.r-project.org/web/packages/e1071/index.html

Donmez, B., Boyle, L. N., & Lee, J. D. (2007). Safety implications of providing real-time feedback to distracted drivers. *Accident; analysis and prevention*, *39*(3), 581-90. doi:10.1016/j.aap.2006.10.003

Duchowski, A. T. (2007). Suggested emprical guidelines. In A. T. Duchowski (Ed.), *Eye tracking methodology: Theory and practice* (2nd ed., pp. 171-180). London: Springer-Verlag.

Durso, F. T., & Dattel, A. R. (2004). SPAM: The real-time assessment of SA. In S. Banbury & S. Tremblay (Eds.), *A cognitive approach to situation awareness: Theory and application* (pp. 137–154). Hampshire, UK: Ashgate Publishing.

Durso, F. T., Hackworth, C. A., Truitt, T. R., Crutchfield, J., Nikolic, D., & Manning, C. A. (1998). Situation awareness as a predictor of performance for en route air traffic controllers. *Air traffic control quarterly*, *6*(1), 1-20.

Endsley, M. R. (1988). Design and evaluation for situation awareness enhancement. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting (32nd)* (Vol. 32, pp. 97-101). Anaheim, CA: Human Factors and Ergonomics Society.

Endsley, M. R. (1995a). Measurement of SA in Dynamic Systems. *Human Factor*, *37*(1), 65-84. Retrieved from http://www.satechnologies.com/Papers/pdf/Measurement of SA in Dynamic Systems.pdf

Endsley, M. R. (1995b). Toward a theory of situation awareness in dynamic systems. *Human factors*, *37*(1), 32-64.

Engström, J., & Victor, T. (2010). Real-time distraction countermeasures. In M. A. Regan, J. D. Lee, & K. L. Young (Eds.), *Driver distraction: Theory, effects, and mitigation* (pp. 465-484). Boca Raton, FL: CRC Press, Taylor & Francis Group.

Engström, J., Johansson, E., & Östlund, J. (2005). Effects of visual and cognitive load in real and simulated motorway driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, *8*(2), 97-120. doi:10.1016/j.trf.2005.04.012

Fisher, R. A. (1938). The statistical utilizaion of multiple measurements. *Annuals of Eugenics*, *8*, 376-386.

Fletcher, L. S. (2008). *An automated co-driver for advanced driver assistance systems: The next step in road safety*. Anstrilian National University.

Fuller, R. (1981). Determinants of time headway adopted by truck drivers. *Ergonomics*, *24*(6), 463-474. doi:10.1080/00140138108924868

Fuller, R. (2005). Towards a general theory of driver behaviour. *Accident Analysis & Prevention*, *37*(3), 461-472. doi:10.1016/j.aap.2004.11.003

Green, D. M., & Swet, J. A. (1988). *Signal detection theory and psychophysics*. New York: Wiley.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task load Index): Reault of emplirical and theoretical research. *Human mental workload* (pp. 139-183). Amsterdam: North-Holland.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). Model Assessment and Selection. *The Elements of Statisical Learning:Data Mining, Inference, and Prediction* (2nd ed., Vol. 2, pp. 219-259). New York: Springer-Verlag.

Hauland, G. (2002). *Measuring team situation awareness in trainging of en-route air traffic control-process oriented measures for experimental studies*. Risø National Laboratory, Roskilde. Retrieved from https://docs.google.com/viewer?url=http://130.226.56.153/rispubl/SYS/syspdf/ris-r-1343.pdf

Hoc, J. M., & Amalberti, R. (1995). Diagnosis: Some theoretical questions raised by applied research. *Cahiers de psychologie cognitive*, *14*(1), 73-101. Association pour la diffusion des recherches en sciences cognitives. Retrieved from http://cat.inist.fr/?aModele=afficheN&cpsidt=3413259

Horrey, W. J., & Simons, D. J. (2007). Examining cognitive interference and adaptive safety behaviours in tactical vehicle control. *Ergonomics*, *50*(8), 1340-50. doi:10.1080/00140130701318889

Horrey, W. J., & Wickens, C. D. (2004). Driving and side task performance: The effects of display clutter, separation, and modality. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *46*(4), 611-624. doi:10.1518/hfes.46.4.611.56805

Horrey, W. J., Wickens, C. D., & Consalus, K. P. (2006). Modeling drivers' visual attention allocation while interacting with in-vehicle technologies. *Journal of experimental psychology. Applied*, *12*(2), 67-78. doi:10.1037/1076-898X.12.2.67

Hsu, C.-wei, & Lin, C.-jen. (2002). A comparison of methods for multiclass support vector machines. *IEEE transactions on neural networks / a publication of the IEEE Neural Networks Council*, *13*(2), 415-25. doi:10.1109/72.991427

Hsu, C.-wei, Chang, C.-chung, & Lin, C.-jen. (2003). A Practical Guide to Support Vector Classification. *Bioinformatics*. Retrieved from http://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf

Hui, X.-feng, & Sun, J. (2006). An Application of Support Vector Machine to Companies ' Financial Distress Prediction *, (70573030), 274 - 282.

Iglewicz, B. (1983). Robust scale estimators and confidence intervals for location. In D. C. Hoaglin, F. Mosteller, & J. W. Tukey (Eds.), *Understanding robust and exploratory data analysis*. New York: Wiley.

Japkowicz, N., & Shah, M. (2011a). Error estimation. *Evaluating learning algrithms: A classification perspective* (pp. 161-205). New York, NY: Cambridge University Press.

Japkowicz, N., & Shah, M. (2011b). Performance Measures I. *Evaluating learning algrithms: A classification perspective* (pp. 74-110). Cambridge, MA.

Jin, S., & Kaber, D. B. (2009). The role of driver cognitive abilities and distractions in situation awareness and performance under hazard conditions. *The proceedings of the IEA 2009 17th World Congress on Ergonomics*. Beijing, China.

Jones, D. G., & Endsley, M. R. (2004). Use of real-time probes for measuring situation awareness. *International Jornal of Aviation Psychology*, *14*(4), 343-367.

Jones, D. G., & Kaber, D. B. (2004). Situation awareness measurement and the situation awareness global assessment technique. In N. A. Stanton, A. Hedge, K. Brookhuis, E. SalasHal, & W. Hendrick (Eds.), *Handbook of Human Factors and Ergonomics Methods* (pp. 42-1~42-8). Boca Raton, USA: CRC Press.

Kaber, D. B., & Perry, C. M. (2007). Workload state classification with automation during simulated air traffic control. *International Journal of Aviation Psychology*, *17*(4), 371-390. doi:10.1080/10508410701527860

Kaber, D. B., Onal, E., & Endsley, M. R. (2000). Design of automation for telerobots and the effect on performance, operator situation awareness, and subjective workload. *Human Factors and Ergonomics in Manufacturing*, *10*(4), 409-430. doi:10.1002/1520-6564(200023)10:4<409::AID-HFM4>3.3.CO;2-M

Karatzoglou, A., Meyer, D., & Hornik, K. (2006). Support vecor machine in R. *Journal Of Statistical Software*, *15*(9).

Karlsson, R. (2004). *Evaluating Driver Distraction Countermeasures*. Linköpings universitet, Sweden.

Kecman, V. (2005). Support Vector Machines – An Introduction. In L. Wang (Ed.), *Support vector machines: Theory and applications (Studies in Fuzziness and Soft Computing)* (Vol. 47, pp. 1-47). Berlin Heidelberg: Springer-Verlag. doi:978-3-540-24388-5

Kennedy, R. S., Lane, N. E., Berbaum, K. S., & Lilienthal, M. G. (1993). Simulator sickness questionnaire: an enhanced method for quantifying simulator sickness. *International Journal of Aviation Psychology, 3*(3), 203-220.

Klauer, S. G., Dingus, T. A., Neale, V. L., Sudweeks, J., & Ramsey, D. J. (2006). *The impact of driver inattention on near-crash/crask risk: An analysis using the 100- car naturalistic driving study data*. Blacksburg, VG. doi:DOT HS 810 594

Kohavi, R. (1995). A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection. *Methodology*.

Kutila, M. H., Jokela, M., Mäkinen, T., Viitanen, J., Markkula, G., & Victor, T. (2007). Driver cognitive distraction detection: Feature estimation and implementation. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 221*, 1027-1040. doi:10.1243/09544070JAUTO332

Lachenburch, P. A., & Goldstein, M. (1979). Discriminant analysis. *Society, 35*(1), 69-85. Retrieved from http://www.jstor.org/pss/2529937

Larsson, P., & Victor, T. (2008). Method and arrangement for interpreting a subjects head and eye activity. Retrieved from http://www.freepatentsonline.com/7460940.html

Lee, J. D. (2006). Driving Distraction. In R. S. Nickerson (Ed.), *Reviews of human factors and ergonomics* (pp. 173-218). Santa Monica, CA: Human Factors and Ergonomics Society.

Lee, J. D., Regan, M. A., & Young, K. L. (2009). What drives distraction? distraction as a breakdown of multilevel control. In M. A. Regan, J. D. Lee, & K. L. Young (Eds.), *Driver distraction: Theory, effects, and mitigation* (pp. 42-56). Boca Raton, FL: CRC Press, Taylor & Francis Group.

Lee, J. D., Reyes, M. L., Liang, Y., & Lee, Yi-Ching. (2007). *SAfety VEhicles using adaptive Interface Technology (Task 5): Algorithms to assess cognitive distraction*. Retrieved from http://www.volpe.dot.gov/hf/roadway/saveit/docs.html

Lee, Yi-Ching, Lee, J. D., & Boyle, L. N. (2007). Visual attention in driving: The effects of cognitive load and visual disruption. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 49*(4), 721-733. doi:10.1518/001872007X215791

Liang, Y. (2009). Detecting driver distraction. Retrieved from http://ir.uiowa.edu/etd/248.

Liang, Y., & Lee, J. D. (2010). Combining cognitive and visual distraction: Less than the sum of its parts. *Accident; analysis and prevention*, *42*(3), 881-90. Elsevier Ltd. doi:10.1016/j.aap.2009.05.001

Liang, Y., Reyes, M. L., & Lee, J. D. (2007). Real-time detection of driver cognitive distraction using support vector machines. *IEEE Transactions on Intelligent Transportation Systems*, *8*(2), 340-350. doi:10.1109/TITS.2007.895298

Liu, Y.-C. (2001). Comparative study of the effects of auditory, visual and multimodality displays on drivers' performance in advanced traveller information systems. *Ergonomics*, *44*(4), 425-42. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/11291824

Ma, R., & Kaber, D. B. (2005). Situation awareness and workload in driving while using adaptive cruise control and a cell phone. *International Journal of Industrial Ergonomics*, *35*(10), 939-953. doi:10.1016/j.ergon.2005.04.002

Maltz, M., & Shinar, D. (2007). Imperfect in-vehicle collision avoidance warning systems can aid distracted drivers. *Transportation Research Part F: Traffic Psychology and Behaviour*, *10*(4), 345-357. doi:10.1016/j.trf.2007.01.002

Masters, T. (1993). *Practical neural network recipes in C++*. San Diego: Academic Press.

Matthews, G. M., Bryant, D. J., Webb, R., & Harbluk, J. L. (2001). Model for situation awareness and driving: Application to analysis and research for intelligent transportation systems. *Transportation research record*, (1779), 26-32. doi:0361-1981

McPhee, L. C., Scialfa, C. T., Dennis, W. M., Ho, G., & Caird, J. K. (2004). Age differences in visual search for traffic signs during a simulated conversation. *Human Factors*, *46*(4), 674-685. Human Factors and Ergonomics Society.

Menard, S. W. (1995). *Quantitative applications in the social sciences: Applied logistic regression analysis*. (D. C. Laughton, Ed.) (2nd ed.). Thousand Oaks, CA: SAGE Publications.

Merat, N., Anttila, V., & Luoma, J. (2005). Comparing the driving performance of average and older drivers: The effect of surrogate in-vehicle information systems. *Transportation Research Part F: Traffic Psychology and Behaviour*, *8*(2), 147-166. doi:10.1016/j.trf.2005.04.011

Michon, J. A. (1985). A critical view of driver behavior models: What do we know, what should we do? In L. Evans & R. Schwing (Eds.), *Human behavior and traffic safety* (pp. 485-520). New York- London: Plenum Press.

Min, J. H., & Lee, Young-Chan. (2005). Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters. *Expert Systems with Applications*, *28*(4), 603-614. doi:10.1016/j.eswa.2004.12.008

Nakanishi, H., & Sato, Y. (1985). The performance of the linear and quadratic discriminant functions for three types of non-normal distribution. *Communications in Statistics - Theory and Methods*, *14*(5), 37-41. doi:10.1080/03610928508828970

Nakayama, O., Futami, T., Nakamura, T., & Boer, E. R. (1999). Development of a steering entropy method for evaluating driver workload. *Proceedings. JSAE Annual Congress* (pp. 5-8). Detroit, Michigan. doi:10.4271/1999-01-0892

Oliver, N., Garg, a, & Horvitz, E. (2004). Layered representations for learning and inferring office activity from multiple sensory channels. *Computer Vision and Image Understanding*, *96*(2), 163-180. doi:10.1016/j.cviu.2004.02.004

Peduzzi, P., Concato, J., Kemper, E., Holford, T. R., & Feinstein, A. R. (1996). Study of the number of events per variable in Logistic Regression Analysis. *Journal of Clinical Epidemiology*, *49*(12), 1373-1379.

Platt, J. C. (1999). Fast training of support vector machines using sequential minimal optimization. In B. Schölkopf, C. J. C. Burges, & A. J. Smola (Eds.), *Advances in Kernel Methods- Support Vector Learning* (pp. 185-208). Cambridge, MA: MIT Press.

Platt, J. C. (2000). Probabilities for SV Machines. In A. Smola, P. Bartlett, B. Schölkopf, & D. Schuurmans (Eds.), *Advances in Large Margin Classifiers* (pp. 62-72). Cambridge, MA: MIT Press.

Rasmussen, J. (1983). Skills, rules and knowledge in aircraft maintenance: Errors in context. *IEEE Transactions on systems, man, and cybernetics*, *13*(3), 257-266. doi:0018-9472

Recarte, M. A., & Nunes, L. M. (2003). Mental workload while driving: effects on visual search, discrimination, and decision making. *Journal of Experimental Psychology: Applied*, *9*(2), 119-137. doi:10.1037/1076-898X.9.2.119

Regan, M. A., Young, K. L., Lee, J. D., & Gordon, C. P. (2009). Source of drivers distraction. In M. A. Regan, J. D. Lee, & K. L. Young (Eds.), *Driver distraction: Theory, effects, and mitigation* (pp. 249-279). Boca Raton, FL: CRC Press, Taylor & Francis Group.

Sarle, W. S. (2002). Neural Network FAQ. *Periodic posting to the Usenet newsgroup comp.ai.neural-nets*. Retrieved 2011, from ftp://ftp.sas.com/pub/neural/FAQ.html

Senders, J. W., Kristofferson, A. B., Levison, W. H., Dietrich, C. W., & Ward, J. L. (1967). The attentional demand of automobile driving. *Highway Research Record*, (195), 15-33. Retrieved from http://pubsindex.trb.org/view.aspx?id=663847

Sever, M., Lajovic, J., & Rajer, B. (2005). Robustness of the Fisher ' s Discriminant Function to Skew-Curved Normal Distribution. *International Conference of Applied Statistics* (Vol. 2, pp. 231-242).

Shen, K.-Q., Ong, C.-J., Li, X.-P., & Wilder-Smith, E. P. V. (2007). Feature selection via sensitivity analysis of SVM probabilistic outputs. *Machine Learning*, *70*(1), 1-20. doi:10.1007/s10994-007-5025-7

Sltelli, A., Tarantola, S., Campolongo, F., & Ratto, M. (2004). *Sensitivity Analysis in practice: a guide to assessing scientific models*. Chichester, England: John Wiley & Sons.

Statnikov, A., Hardin, D., & Aliferis, C. (2006). Using SVM Weight-Based Methods to Identify Causally Relevant and Non-Causally Relevant Variables. *Neural Information Processing Systems (NIPS) 2006 Workshop on Causality and Feature Selection*. Vancouver, Canada.

Strayer, D. L., & Drews, F. A. (2004). Profiles in driver distraction: effects of cell phone conversations on younger and older drivers. *Human factors*, *46*(4), 640-9. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/15709326

Strayer, D. L., & Johnston, W. A. (2001). Driven to distraction: Dual-task studies of simulated driving and conversing on a cellular telephone. *Psychological Science*, *12*(6), 462 - 466. Blackwell Publishing on behalf of the Association for Psychological Science. Retrieved from http://www.jstor.org/stable/40063671

Strayer, D. L., Drews, F. A., & Johnston, W. A. (2003). Cell phone-induced failures of visual attention during simulated driving. *Journal of Experimental Psychology: Applied*, *9*(1), 23-32. doi:10.1037/1076-898X.9.1.23

Stutts, J. C., Reinfurt, D. W., Staplin, L., & Rodgman, E. A. (2001). *The role of driver distraction in crashes*. *Annual proceedings / Association for the Advancement of Automotive Medicine. Association for the Advancement of Automotive Medicine* (Vol. 45). Washington,D.C. Retrieved from http://www.aaafoundation.org/pdf/distraction.pdf

Tango, F., & Botta, M. (2009). Evaluation of Distraction in a Driver-Vehicle- Environment Framework : An Application of Different Data-Mining Techniques. (P. Perner, Ed.)*Lecture notes in computer science*, *5633*, 176-190. Springer-Verlag. doi:10.1007/978-3-642-03067-3

Taylor, R. M. (1990). Situational awareness rating technique (SART): The development of a tool for aircrew systems design. *Situational Awareness in Aerospace Operations (AGARD-CP-478)* (pp. 3/1-3/17). Copenhagen, Denmark: NATO-Advisory Group for Aerospace Research and Development.

Taylor, R. M., & Selcon, S. J. (1990). Subjective measurement of situational awareness. In Queinnec & Daniellous (Eds.), *Designing for everyone, Proceedings of the 11th Congress of the International Ergonomics Association* (pp. 789-791). London: Taylor & Francis.

Thomas, K. P., Guan, C., Lau, C. T., Vinod, a P., & Ang, K. K. (2009). A new discriminative common spatial pattern method for motor imagery brain-computer interfaces. *IEEE transactions on bio-medical engineering*, *56*(11 Pt 2), 2730-3. doi:10.1109/TBME.2009.2026181

Vapnik, V. N. (2000). Methods of pattern recognition. In M. Jordan, J. F. Lawless, S. L. Lauritzen, & V. Nair (Eds.), *Statistics for engineering and information science: The nature of Statistical learning theory* (2nd ed., pp. 123-170). New York: Springer-Verlag.

Victor, T. (2005). *Keeping Eye and Mind on the Road*. Uppsala University. Retrieved from http://urn.kb.se/resolve?urn=urn:nbn:se:uu:diva-6241

Victor, T., Harbluk, J. L., & Engström, J. (2005). Sensitivity of eye-movement measures to in-vehicle task difficulty. *Transportation Research Part F: Traffic Psychology and Behaviour*, *8*(2), 167-190. doi:10.1016/j.trf.2005.04.014

Wang, Y., Mehler, B., Reimer, B., Lammers, V., D'Ambrosio, L. a, & Coughlin, J. F. (2010). The validity of driving simulation for assessing differences between in-vehicle informational interfaces: A comparison with field testing. *Ergonomics*, *53*(3), 404-20. doi:10.1080/00140130903464358

Weiss, S. M., & Kulikowski, C. A. (1991). *Computer systems that learn: classification and prediction methods from statistics, neural nets, machine learning, and expert systems*. San Mateo, CA: Morgan Kaufman.

Wickens, C. D. (1984). Processing resource in attention. In R. Parasuraman & R. Davies (Eds.), *Varieties of Attention* (pp. 63-101). Orlando,FL: Academic Press.

Wickens, C. D. (2002). Multiple resources and performance prediction. *Theoretical Issues in Ergonomics Science*, *3*(2), 159-177. doi:10.1080/14639220210123806

Wickens, C. D. (2008). Multiple Resources and Mental Workload. *Human Factors*, *50*(3), 449-455. doi:10.1518/001872008X288394.

Wickens, C. D., Lee, J. D., Liu, Y., & Becker, S. E. (2004). Decision making. In J. Leah (Ed.), *An introduction to human factors egineering* (2nd ed., pp. 156-183). Upper Saddle River, NJ: Pearson Education, Inc.

Wierwille, W. W. (1993). Visual and manual demands of in-car controls and displays. In B. Peacock & W. Karwowski (Eds.), *Automotive Ergonomics* (pp. 299-320). London: Taylor & Francis.

Willems, B., & Truitt, T. R. (1999). *Implicaitons of reduced involvment in en route air traffic control*. Atlantic City International Airport, NJ. doi:DOT/FAA/CT-TN99/22

Wilson, G. F., & Russell, C. A. (2003). Operator runctional state classification using multiple psychophysiological features in an air traffic control task. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *45*(3), 381-389. Human Factors and Ergonomics Society. doi:10.1518/hfes.45.3.381.27252

de Winter, J. C. F., de Groot, S., Mulder, M., Wieringa, P. A., Dankelman, J., & Mulder, J. A. (2009). Relationships between driving simulator performance and driving test results. *Ergonomics*, *52*(2), 137-53. doi:10.1080/00140130802277521

Young, R., Aryal, B., Muresan, M., Ding, X., Oja, S., & Simpson, S. N. (2005). Road-to-lab: Validation of the static load test for predicting on-road driving performance while using advanced in-vehicle information and communication devices. *Proceeding of the third international driving symposium on Human Factors in driver assessment* (pp. 240-254).

Zhang, Y., Jin, S., Garner, M., Mosaly, P., & Kaber, D. B. (2009). The effects of aging and cognitive stress disposition on driver situation awareness and performance in hazardous conditions. *Proceedings of the IEA 2009 17th World Congress on Ergonomics*. Beijing, China.

APPENDIX

Appendix: Goal-Directed Tasks Analysis (GDTA) and SA probing questions

Main Goal: Following the lead vehicle

Sub-goal 1: Plan navigation

Sub-Sub-goal 1. 1: Driving on the desired course to destination

Decision 1.1.1: How long have I driven?

Information needs:

- Duration of the current drive
- Distance of the current drive
- Traffic sign information –Decision 3.1.3

SA Question 1. How long have we already driven? (L2)

SA Question 2. How far have we already driven? (L2)

Decision 1.1.2: How long do I need to drive?

Information needs:

- Duration of the current drive –Decision 1.1.1
- Distance of the current drive – Decision 1.1.1

SA Question 3. Can you estimate how long before we finish this drive? (L3)

SA Question 4. Can you estimate how far before we finish this drive? (L3)

Decision 1.1.3: Did I see any sign indicating how long to the destination?

Information needs:

Traffic sign information –Decision 3.3.3

SA Question 5. Did you see any sign showing our distance to the destination? (L1)

Decision 1.1.4: Do I see the finish line?

Information needs: Traffic sign information –Decision 3.3.3

SA Question 6. Do you see the finish line? (L1)

SA Question 7. How far are we from the finish line? (L1)

SA Question 8. How long does it take us to reach the finish line? (L3)

Sub-goal 2: Determine the state of own vehicle

Sub-Sub-goal 2. 1: Observe current kinematic parameters of own vehicle

Decision 2.1.1: What is the position of my vehicle?

Information needs:

- Lane (left land or right lane)
- Lane position (left side, middle, or right side)

SA Question 9. Which lane are we currently in? (L1)

SA Question 10. How far away is our car to left/right lane dividing line? (L1)

Decision 2.1.2: What speed is my vehicle travelling?

Information needs: Current speed

SA Question 11. What is our current speed? (L1)

Decision 2.1.3: Am I travelling below or above the current speed limit?

Information needs: Current speed –Decision 2.1.2

Traffic sign information –Decision 3.3.3

SA Question 12. Are we travelling above or below the speed limit? (L2)

Decision 2.1.4: Which direction is my vehicle travelling?

Information needs: Current steering wheel position

SA Question 13. Are we currently travelling straight/ turning to right/left? (L1)

SA Question 14. Are we going cross lane (L2)?

Sub-Sub-goal 2. 2: Determine future state of own vehicle

Decision 2.2.1: What speed will my vehicle travel (when no passing)?

Current speed –Decision 2.1.2

Grade of the road –Decision 3.3.2

SA Question 15. If we maintain current acceleration, is our speed going to increase, decrease, or no-change? (L3)

SA Question 16. To keep the same speed, do you need to accelerate or decelerate? (L3)

SA Question 17. If we maintain current acceleration, are we going to drive below or above the current speed limit? (L3)

Decision 2.2.2: What position will my vehicle be in the next few seconds (when no passing)?

Information needs: Current speed of my vehicle –Decision 2.1.2

- Current position of my vehicle –Decision 2.1.1
- Steering wheel position –Decision 2.1.4
- Direction of the road

SA Question 18. If we maintain our current direction, will we remain in the same lane? (L3)

SA Question 19. If we maintain our current direction, will we remain in the same lane position? (L3)

SA Question 20. If we maintain our current direction, will we hit the shoulder or median? (L3)

SA Question 21. Are we going to turn to right/left soon? (L3)

Sub-goal 3: Determine the state of driving environment

Sub-Sub-goal 3. 1: Observe and determine lead vehicle behavior

Decision 3.1.1: What is the relative position of lead vehicle to my vehicle?

Information needs: Distance from my vehicle to lead vehicle

SA Question 22. How far away from our car is it to lead vehicle? (L1)

Decision 3.1.2: What is the lateral position of lead vehicle to my vehicle?

Information needs: Lateral position of lead vehicle

SA Question 23. Is lead vehicle travelling in the center of a lane? (L1)

SA Question 24. Is lead vehicle moving toward a lane boundary? (L1)

SA Question 25. Is lead vehicle crossing a lane dividing line? (L2)

SA Question 26. Which lane is lead vehicle travelling in? (L1)

Decision 3.1.3: What is the relative speed of lead vehicle to my vehicle?

Information needs: Relative speed difference of lead vehicle to my vehicle

SA Question 27. What is the relative speed to lead vehicle? (L1)

SA Question 28. Are we driving faster/slower/at the same speed as lead vehicle? (L1)

SA Question 29. Are we loosing or gaining on lead vehicle? (L2)

Decision 3.1.4: Are the brake lights of lead vehicle on?

Information needs: Brake light of lead vehicle

SA Question 30. Are the brake lights of lead vehicle on? (L1)

Decision 3.1.5: What is the speed of lead vehicle?

- Speed of my vehicle –Decision 2.1.2
- Speed difference to lead vehicle –Decision 3.1.3
- Brake light of lead vehicle –Decision 3.1.4
- Traffic sign information –Decision 3.3.3

SA Question 31. What is the speed of lead vehicle? (L2)

SA Question 32. Is lead vehicle speeding up, slowing down, or traveling at a constant speed? (L2)

SA Question 33. Is the lead vehicle driving above/below the speed limit? (L2)

Decision 3.1.6: What is the headway time from my vehicle to lead vehicle?

Information needs:

- Distance from my vehicle to lead vehicle –Decision 3.1.1
- Relative speed to lead vehicle –Decision 3.1.3

SA Question 34. What is the headway time from our vehicle to lead vehicle? (L2)

Decision 3.1.7: How will the distance to lead vehicle change in the next few seconds?

Information needs:

- Distance from my vehicle to lead vehicle –Decision 3.1.1.
- Speed difference between my vehicle and lead vehicle –Decision 3.1.3.
- Brake light of lead vehicle –Decision 3.1.4.

SA Question 35. Will the headway distance to the leading vehicle increase? (L3)

Sub-Sub-goal 3. 2: Perceive and determine the states of vehicles in adjacent lane.

Decision 3.2.1: What is the relative position of traffic to my vehicle?

Information needs: Distance from my vehicle to the vehicles in adjacent lanes

SA Question 36. Are there any vehicles in the right/left lane adjacent to our car? (L1)

SA Question 37. Is there any vehicle right beside us? (L1)

SA Question 38. Is there a vehicle close and behind us? (L1)

SA Question 39. Is there a vehicle close and in front of us? (L1)

SA Question 40. Is the vehicle in the adjacent lane and in front of us close to our car? (L2)

SA Question 41. Is the vehicle in the adjacent lane and behind us close to our car? (L2)

Decision 3.2.2: What is the relative speed of the traffic compared to my vehicle?

Information needs: Relative speed to the vehicles in adjacent lane

SA Question 42. Is the closest vehicle in the adjacent lane moving faster/slower than us? (L2)

SA Question 43. In the adjacent lane, is there a vehicle driving towards us from behind? (L2)

SA Question 44. In the adjacent lane, is there a vehicle in front of us and moving slower than our car? (L2)

Decision 3.2.3: What is the speed of the traffic?

Information needs: Relative speed of my vehicle to the vehicles in adjacent lanes – Decision 3.2.2.

Speed of my vehicle –Decision 2.1.2.

SA Question 45. Is speed of the closest vehicle in the adjacent lane and in front of us above/below the current speed limit? (L2)

SA Question 46. Is speed of the vehicle right beside us above/below the current speed limit? (L2)

SA Question 47. Is speed of the closest vehicle behind us above/below the current speed limit? (L2)

Decision 3.2.4: Is my vehicle going to pass any traffic any time soon?

Information needs:

- Distance to other vehicles in adjacent lanes –Decision 3.2.1.
- Speed difference to vehicles in adjacent lanes –Decision 3.2.2.

SA Question 48. Are we going to pass any vehicles in an adjacent lane in the near future? (L3)

SA Question 49. How long will it take for us to pass them? (L3)

Decision 3.2.5: Is there any vehicle in adjacent lanes that is going to passing us?

Information needs

- Distance to the vehicles in adjacent lanes –Decision 3.2.1.
- Speed difference to vehicles in adjacent lanes –Decision 3.2.2.

SA Question 50. Are we going to be passed by any vehicles in an adjacent lane in the near future? (L3)

SA Question 51. How long will it take for the closest vehicle to pass us? (L3)

Sub-Sub-goal 3. 3: 3.3. Perceive roadway, markings, signage and signals

Decision 3.3.1: Is the road turning to the right/left?

Information needs: Curvature of the road

SA Question 52. Is the road turning to the right/left right now? (L1)

SA Question 53. Dose the road extend to the right/left? (L1)

Decision 3.3.2: Is there an uphill/downhill slope?

Information needs: Grade of the road

SA Question 54. Are we going uphill or downhill? (L1)

Decision 3.3.3: What is the current speed limit?

Information needs: Speed limit sign

SA Question 55. What is the current speed limit? (L1)

Decision 3.3.4: How has the speed limit changed?

Information needs:

- Speed limit sign –Decision 3.3.3
- Previous speed limit signs

SA Question 56. Have speed limits changed in this drive? (L2)
SA Question 57. Does the speed limit increase in this drive? (L2)
SA Question 58. What was previous speed limit for this drive? (L2)

Decision 3.3.5: What traffic signs have I seen?
Information needs: Traffic sign information

SA Question 59. what was the last road sign you saw? (speed limit, route signs, etc) (L1)
SA Question 60. What did the last road sign say? (L1)
SA Question 61. About how long ago did we pass the last sign? (L2)
SA Question 62. If you saw a child abduction alert, what type of the car does the suspect drive? (L1)
SA Question 63. Which highway are we currently travelling on? (L1)

Decision 3.3.6: What traffic signs are in view?
Information needs: Traffic sign information

SA Question 64. Is there a (speed limit, turning, route, etc) sign in view?
SA Question 65. If you can see any traffic sign, how far is the nearest one from us? (L2)
SA Question 66. When will we reach the nearest traffic sign? (L3)

Sub-goal 4: Execute driving action/maneuver

Sub-Sub-goal 4. 1: 4.1. Maintain speed limit

Decision 4.1.1: How can I maintain the speed limit?
Information needs:

- Speed of my vehicle –Decision 2.1.2.
- Speed limit sign information –Decision 3.3.3
- Grade of road –Decision 3.3.2

SA Question 67. Do you need to accelerate/decelerate to match the speed limit? (L2)
SA Question 68. Do you need to use the accelerator/brake to maintain your current speed? (L2)
SA Question 69. How long will it take for you to match the speed limit? (L3)

Sub-Sub-goal 4. 2: Turn right/left along the road curve

Decision 4.2.1: Do I need to turn the steering wheel to follow the road curvature?
Information needs:

- Direction of travel of my vehicle –Decision 2.1.4.
- Position of my vehicle –Decision 2.1.1.
- Speed of my vehicle –2.1.2.
- Curvature of the road –Decision 3.1.1

SA Question 70. Will you be steering to the right or left to match the road curve? (L3)

SA Question 71. 7Which direction are you going to turn the steering wheel next? (L3)

Sub-Sub-goal 4. 3: Following lead vehicle

Decision 4.3.1: Is the distance between my vehicle and lead vehicle safe?

Decision 4.3.2: I need to accelerate to catch up with lead vehicle?

Information needs

- Relative position to lead vehicle –Decision 3.1.1
- Speed difference between my vehicle and lead vehicle –Decision 3.1.2.

SA Question 72. What is the headway time to the leave vehicle? (L2)

SA Question 73. If you maintain your current speed, is it possible that we will have a collision with lead vehicle? (L3)

SA Question 74. If you maintain your current speed, will our distance to lead vehicle increase? (L3)

Decision 4.3.3: Do I need to accelerate to catch up with lead vehicle?

Information needs:

- Distance to lead vehicle-Decision 3.1.1.
- Speed difference between my vehicle and lead vehicle –Decision 3.1.2.
- Brake light of lead vehicle –Decision 3.1.3.
- Speed of my vehicle –Decision 2.1.2.

SA Question 75. Do you need to accelerate to follow lead vehicle? (L2)

SA Question 76. How long will it take us to catch up with lead vehicle? (L3)

Decision 4.3.4: Do I need to decelerate to back off from lead vehicle?

Information needs:

- Distance to lead vehicle-Decision 3.1.1.
- Speed difference between my vehicle and lead vehicle –Decision 3.1.2.
- Brake light of lead vehicle –Decision 3.1.3.
- Speed of my vehicle –Decision 2.1.2.

SA Question 77. Do you need to brake to avoid a collision with lead vehicle? (L2)

SA Question 78. How long you have to brake to avoid a collision with lead vehicle? (L3)

Decision 4.3.5: Is the lead vehicle going to change lane?

Information needs:

- Travelling direction of the lead vehicle
- Lane position of the lead vehicle

SA Question 79. Is the lead vehicle going to change lane? (L2)

SA Question 80. How long will it take for lead vehicle to complete a lane change? (L3)

Decision 4.3.6: Do I need to change lane?

Information needs:

- Lateral position of the lead vehicle –Decision 3.1.2.
- Lateral position of my vehicle –Decision 2.1.1.

SA Question 81. Do we need to change lane right now? (L2)
SA Question 82. Which lane do we need to change to? (L2)
Decision 4.3.7: How long does it take to complete lane changing?
Information needs:
- Travelling direction of my vehicle –Decision 2.1.4.
- Lane position of my vehicle –Decision 2.1.1.
- Curvature of the road –Decision 3.3.1.

SA Question 83. Do you need to turn the steering wheel next? (L3)
SA Question 84. Which direction are you going to turn the steering wheel?
SA Question 85. How long will it take for our vehicle to complete a lane change with the current steering angle? (L3)

Main Goal: Passing slowing vehicles safely in the simulated driving environment
Sub-goal 1: Plan navigation
Sub-Sub-goal 1. 1: Driving on the desired course to destination
Decision 1.1.1: How long have I driven?
Information needs:
- Duration of the current drive
- Distance of the current drive
- Traffic sign information –Decision 3.1.3.

SA Question 1. How long have we already driven? (L2)
SA Question 2. How far have we already driven? (L2)
Decision 1.1.2: How long do I need to drive?
Information needs:
- Duration of the current drive –Decision 1.1.1.
- Distance of the current drive –1.1.1.

SA Question 3. Can you estimate how long before we finish this drive? (L3)
SA Question 4. Can you estimate how far before we finish this drive? (L3)
Decision 1.1.3: Did I see any sign indicating how long to the destination?
Information needs: Traffic sign information –Decision 3.3.3.
SA Question 5. Did you see any sign showing our distance to the destination? (L1)
Decision 1.1.4: Do I see the finish line?
Information needs: Traffic sign information –Decision 3.3.3.
SA Question 6. Do you see the finish line? (L1)
SA Question 7. How far are we from the finish line? (L1)
SA Question 8. How long does it take us to reach the finish line? (L3)
Sub-goal 2: Determine the state of own vehicle
Sub-Sub-goal 2. 1: Observe current kinematic parameters of own vehicle
Decision 2.1.1: What is the position of my vehicle?
Information needs:
- Lane (left land or right lane)

- Lane position (left side, middle, or right side)

SA Question 9. Which lane are we currently in? (L1)

SA Question 10. How far away is our car to left/right lane dividing line? (L1)

Decision 2.1.2: What speed is my vehicle travelling?

Information needs: Current speed

SA Question 11. What is our current speed? (L1)

Decision 2.1.3: Am I travelling below or above the current speed limit?

Information needs:

- Current speed –Decision 2.1.2.
- Traffic sign information –Decision 3.3.3.

SA Question 12. Are we travelling above or below the speed limit? (L2)

Decision 2.1.4: Which direction is my vehicle travelling?

Information needs: Current steering wheel position

SA Question 13. Are we currently travelling straight/ turning to right/left? (L1)

SA Question 14. Are we going cross lane (L2)?

Sub-Sub-goal 2. 2: Determine future state of own vehicle

Decision 2.2.1: What speed will my vehicle travel (when no passing)?

Information needs:

- Current speed –Decision 2.1.2.
- Grade of the road –Decision 3.3.2.

SA Question 15. If we maintain current acceleration, is our speed going to increase, decrease, or no-change? (L3)

SA Question 16. To keep the same speed, do you need to accelerate or decelerate? (L3)

SA Question 17. If we maintain current acceleration, are we going to drive below or above the current speed limit? (L3)

Decision 2.2.2: What position will my vehicle be in the next few seconds?

Information needs:

- Current speed of my vehicle –Decision 2.1.2.
- Current position of my vehicle –Decision 2.1.1.
- Steering wheel position –Decision 2.1.4.
- Direction of the road

SA Question 18. If we maintain our current direction, will we remain in the same lane? (L3)

SA Question 19. If we maintain our current direction, will we remain in the same lane position? (L3)

SA Question 20. If we maintain our current direction, will we hit the shoulder or median? (L3)

SA Question 21. Are we going to turn to right/left soon? (L3)

Sub-goal 3: Determine the state of driving environment

Sub-Sub-goal 3. 1: Observe and determine lead vehicle behavior

Decision 3.1.1: What is the relative position of lead vehicle to my vehicle?
Information needs: Distance from my vehicle to lead vehicle
SA Question 22. How far away from our car is it to lead vehicle? (L1)
Decision 3.1.2: What is the lateral position of lead vehicle to my vehicle?
Information needs: Lateral position of lead vehicle
SA Question 23. Is lead vehicle travelling in the center of a lane? (L1)
SA Question 24. Is lead vehicle moving toward a lane boundary? (L1)
SA Question 25. Is lead vehicle crossing a lane dividing line? (L2)
SA Question 26. Which lane is lead vehicle travelling in? (L1)
Decision 3.1.3: What is the relative speed of lead vehicle to my vehicle?
Information needs: Relative speed difference of lead vehicle to my vehicle
SA Question 27. What is the relative speed to lead vehicle? (L1)
SA Question 28. Are we driving faster/slower/at the same speed as lead vehicle? (L1)
SA Question 29. Are we loosing or gaining on lead vehicle? (L2)
Decision 3.1.4: Are the brake lights of lead vehicle on?
Information needs: Brake light of lead vehicle
Are the brake lights of lead vehicle on? (L1)

Decision 3.1.5: What is the speed of lead vehicle?
Information needs:

- Speed of my vehicle –Decision 2.1.2.
- Speed difference to lead vehicle –Decision 3.1.3.
- Brake light of lead vehicle –Decision 3.1.4.
- Traffic sign information –Decision 3.3.3.

SA Question 30. What is the speed of lead vehicle? (L2)
SA Question 31. Is lead vehicle speeding up, slowing down, or traveling at a constant speed? (L2)
SA Question 32. Is the lead vehicle driving above/below the speed limit? (L2)
Decision 3.1.6: What is the headway time from my vehicle to lead vehicle?

- Distance from my vehicle to lead vehicle –Decision 3.1.1.
- Relative speed to lead vehicle –Decision 3.1.3.

SA Question 33. What is the headway time from our vehicle to lead vehicle? (L2)
Decision 3.1.7: How will the distance to lead vehicle change in the next few seconds?
Information needs:

- Distance from my vehicle to lead vehicle –Decision 3.1.1.
- Speed difference between my vehicle and lead vehicle –Decision 3.1.3.
- Brake light of lead vehicle –Decision 3.1.4.

SA Question 34. Will the headway distance to the leading vehicle increase? (L3)
Sub-Sub-goal 3. 2: Perceive and determine the states of vehicles in adjacent lane

Decision 3.2.1: What is the relative position of traffic to my vehicle?

Information needs: Distance from my vehicle to the vehicles in adjacent lanes

SA Question 35. Are there any vehicles in the right/left lane adjacent to our car? (L1)

SA Question 36. Is there any vehicle right beside us? (L1)

SA Question 37. Is there a vehicle close and behind us? (L1)

SA Question 38. Is there a vehicle close and in front of us? (L1)

SA Question 39. Is the vehicle in the adjacent lane and in front of us close to our car? (L2)

SA Question 40. Is the vehicle in the adjacent lane and behind us close to our car? (L2)

Decision 3.2.2: What is the relative speed of the traffic compared to my vehicle?

Information needs: Relative speed to the vehicles in adjacent lane

SA Question 41. Is the closest vehicle in the adjacent lane moving faster/slower than us? (L2)

SA Question 42. In the adjacent lane, is there a vehicle driving towards us from behind? (L2)

SA Question 43. In the adjacent lane, is there a vehicle in front of us and moving slower than our car? (L2)

Decision 3.2.3: What is the speed of the traffic?

Information needs:

- Relative speed of my vehicle to the vehicles in adjacent lanes –Decision 3.2.2.
- Speed of my vehicle –Decision 2.1.2.

SA Question 44. Is speed of the closest vehicle in the adjacent lane and in front of us above/below the current speed limit? (L2)

SA Question 45. Is speed of the vehicle right beside us above/below the current speed limit? (L2)

SA Question 46. Is speed of the closest vehicle behind us above/below the current speed limit? (L2)

(1) Is my vehicle going to pass any traffic any time soon? Level 3

Distance to other vehicles in adjacent lanes –3.2.(1)

Speed difference to vehicles in adjacent lanes –3.2.(2)

SA Question 47. Are we going to pass any vehicles in an adjacent lane in the near future? (L3)

SA Question 48. How long will it take for us to pass them? (L3)

Decision 3.2.4: Will any vehicle in an adjacent lane pass us?

Information needs:

- Distance to the vehicles in adjacent lanes –Decision 3.2.1
- Speed difference to vehicles in adjacent lanes –Decision 3.2.2

SA Question 49. Are we going to be passed by any vehicles in an adjacent lane in the near future? (L3)

SA Question 50. How long will it take for the closest vehicle to pass us? (L3)

Sub-Sub-goal 3. 3: Perceive roadway, markings, signage and signals

Decision 3.3.1: Is the road turning to the right/left?
Information needs: Curvature of the road
SA Question 51. Is the road turning to the right/left right now? (L1)
SA Question 52. Dose the road extend to the right/left? (L1)
Decision 3.3.2: Is there an uphill/downhill slope?
Information needs: Grade of the road
SA Question 53. Are we going uphill or downhill? (L1)
Decision 3.3.3: What is the current speed limit?
Information needs: Speed limit sign
SA Question 54. What is the current speed limit? (L1)
Decision 3.3.4: How has the speed limit changed?
Information needs:

- Speed limit sign –Decision 3.3.3.
- Previous speed limit signs

SA Question 55. Have speed limits changed in this drive? (L2)
SA Question 56. Does the speed limit increase in this drive? (L2)
SA Question 57. What was previous speed limit for this drive? (L2)
Decision 3.3.5: What traffic signs have I seen?
Information needs: Traffic sign information
SA Question 58. What was the last road sign you saw? (speed limit, route signs, etc) (L1)
SA Question 59. What did the last road sign say? (L1)
SA Question 60. About how long ago did we pass the last sign? (L2)
SA Question 61. If you saw a child abduction alert, what type of the car does the suspect drive? (L1)
SA Question 62. Which highway are we currently travelling on? (L1)
Decision 3.3.6: What traffic signs are in view?
Information needs: Traffic sign information
SA Question 63. Is there a (speed limit, turning, route, etc) sign in view?
SA Question 64. If you can see any traffic sign, how far is the nearest one from us? (L2)
SA Question 65. When will we reach the nearest traffic sign? (L3)

Sub-goal 4: Execute driving action/maneuver
Sub-Sub-goal 4. 1: Maintain speed limit
Decision 4.1.1: How can I maintain the speed limit?
Information needs:

- Speed of my vehicle –Decision 2.1.2
- Speed limit sign information –Decision 3.3.3
- Grade of road –Decision 3.3.2.

SA Question 66. Do you need to accelerate/decelerate to match the speed limit? (L2)
SA Question 67. Do you need to use the accelerator/brake to maintain your current speed? (L2)

SA Question 68. How long will it take for you to match the speed limit? (L3)

Sub-Sub-goal 4. 2: Turn right/left along the road curve

Decision 4.2.1: Do I need to turn the steering wheel to follow the curvature?

Information needs:

- Direction of travel of my vehicle –Decision 2.1.4.
- Position of my vehicle –Decision 2.1.1.
- Speed of my vehicle –Decision 2.1.2.
- Curvature of the road –Decision 3.1.1

SA Question 69. Will you be steering to the right or left to match the road curve? (L3)

SA Question 70. Which direction are you going to turn the steering wheel next? (L3)

Sub-Sub-goal 4. 3: Following lead vehicle

Decision 4.3.1: I need to accelerate to catch up with lead vehicle?

Information needs:

- Relative position to lead vehicle –Decision 3.1.1.
- Speed difference between my vehicle and lead vehicle –Decision 3.1.2.

SA Question 71. What is the headway time to the leave vehicle? (L2)

SA Question 72. If you maintain your current speed, is it possible that we will have a collision with lead vehicle? (L3)

SA Question 73. If you maintain your current speed, will our distance to lead vehicle increase? (L3)

Decision 4.3.2: Do I need to accelerate to catch up with lead vehicle?

Information needs:

- Distance to lead vehicle-Decision 3.1.1.
- Speed difference between my vehicle and lead vehicle –Decision 3.1.2.
- Brake light of lead vehicle –Decision 3.1.3.
- Speed of my vehicle –Decision 2.1.2.

SA Question 74. Do you need to accelerate to follow lead vehicle? (L2)

SA Question 75. How long will it take us to catch up with lead vehicle? (l3)

Decision 4.3.3: Do I need to decelerate to back off from lead vehicle?

Information needs:

- Distance to lead vehicle-Decision 3.1.1.
- Speed difference between my vehicle and lead vehicle –Decision 3.1.2.
- Brake light of lead vehicle –Decision 3.1.3.
- Speed of my vehicle –Decision 2.1.2.

SA Question 76. Do you need to brake to avoid a collision with lead vehicle? (L2)

SA Question 77. How long you have to brake to avoid a collision with lead vehicle? (L3)

Sub-goal 5: Passing a decelerating lead vehicle

Sub-Sub-goal 5. 1: Identify whether the pass criterion is satisfied

Decision 5.1.1: Has lead vehicle slowed down?

Information needs:

- Relative speed to lead vehicle –Decision 3.1.3.
- Brake light of lead vehicle –Decision 3.1.4.
- Speed of my vehicle –Decision 2.1.2.

SA Question 78. Has lead vehicle slowed down? (L2)

Decision 5.1.2: Is the speed of lead vehicle 10 MPH below the speed limit?

Information needs:

- Speed difference between my vehicle and lead vehicle –Decision 3.1.2.
- Brake light of lead vehicle –Decision 3.1.3.
- Speed of my vehicle –Decision 2.1.2.

SA Question 79. Is the speed of lead vehicle 10 MPH below the speed limit? (L2)

SA Question 80. Do we need to pass lead vehicle? (L2)

Sub-Sub-goal 5. 2: Change lane to the left/right

Decision 5.2.1: Do I have enough time to change lanes before approaching traffic passing my vehicle?

Information needs:

- Distance to the vehicles in adjacent lanes –Decision 3.2.1.
- Speed difference to vehicles in adjacent lanes –Decision 3.2.2.

SA Question 81. How long will it take for the approaching traffic to catch up with me? (L3)

SA Question 82. Are we going to be hit by the vehicle behind if we change lanes right now? (L3)

Decision 5.2.2: Do I have to wait to pass slow traffic or let the approaching traffic pass me?

Information needs:

- Distance to the vehicles in adjacent lanes – Decision 3.2.1.
- Speed difference to vehicles in adjacent lanes –3.2.2.

SA Question 83. How long do we need to wait before changing lanes such that the slow traffic in an adjacent lane will not block us? (L3)

SA Question 84. Are we going to hit a vehicle in front of us if we change lanes right now? (L3)

Decision 5.2.3: What preventive maneuver is needed before changing lane?

Information needs: Conflict information – Decision 4.2.1-4.2.5

SA Question 85. Can we change lane right now?

SA Question 86. How many vehicles may conflict with us if we change lanes now?

SA Question 87. Do we need to accelerate?

SA Question 88. Do we need to decelerate?

SA Question 89. Should we maintain our current speed?

Decision 5.2.4: Do I need accelerate?

Decision 5.2.5: How long do I need to accelerate?

Information needs:

- Distance to lead vehicle –Decision 3.1.1
- Speed of lead vehicle –Decision 3.1.3.
- Distance to the vehicles in adjacent lanes –Decision 3.2.1.
- Speed difference to vehicles in adjacent lanes –Decision 3.2.2.

SA Question 90. Do we need to accelerate? (L2)

SA Question 91. How long do we need to accelerate for? (L3)

Decision 5.2.6: Do I need decelerate?

Decision 5.2.7: When do I need to decelerate?

Information needs:

- Distance to lead vehicle –Decision 3.1.1
- Speed of lead vehicle –Decision 3.1.3.
- Distance to the vehicles in adjacent lanes –Decision 3.2.1.
- Speed difference to vehicles in adjacent lanes –Decision 3.2.2.

SA Question 92. Do we need decelerate? (L2)

SA Question 93. When do we need to decelerate? (L3)

Decision 5.2.8: Can I change lanes right now?
Conflict information –Decision 5.2.1-5.2.3

SA Question 94. Do we need to change lanes right now? (L2)

SA Question 95. Which lane do we need to change to? (L2)

Decision 5.2.9: How long does it take to complete a lane change?

Information needs:

- Travelling direction of my vehicle –Decision 2.1.4
- Lane position of my vehicle –Decision 2.1.1
- Curvature of the road –Decision 3.3.1

SA Question 96. How long will it take to complete a lane change with the current steering angle? (L3)