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Detecting driver distraction

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DETECTING DRIVER DISTRACTION

by

Yulan Liang

An Abstract

Of a thesis submitted in partial fulfillment
of the requirements for the Doctor of
Philosophy degree in Industrial Engineering
in the Graduate College of
The University of Iowa

May 2009

Thesis Supervisor: Professor John D. Lee

ABSTRACT

The increasing use of in-vehicle information systems (IVISs), such as navigation devices and MP3 players, can jeopardize safety by introducing distraction into driving. One way to address this problem is to develop distraction mitigation systems, which adapt IVIS functions according to driver state. In such a system, correctly identifying driver distraction is critical, which is the focus of this dissertation. Visual and cognitive distractions are two major types of distraction that interfere with driving most compared with other types. Visual and cognitive distraction can occur individually or in combination. The research gaps in detecting driver distraction are that the interactions of visual and cognitive distractions have not been well studied and that no accurate algorithm/strategy has been developed to detect visual, cognitive, or combined distraction.

To bridge these gaps, the dissertation fulfilled three specific aims. The first aim demonstrated the layered algorithm developed based on data mining methods could improve the detection of cognitive distraction from my previous studies. The second aim developed estimation algorithms for visual distraction and demonstrated a strong relationship of the estimated distraction with the increased risk of real crashes using the naturalistic data. The third objective examined the interaction of visual and cognitive distractions and developed an effective strategy to identify combined distraction. Together these aims suggest that driver distraction can be detected from performance indicators using appropriate quantitative methods. Data mining techniques represent a promising category of methods to construct such detection algorithms. When combined in a sequential way, visual distraction dominates the effects of distraction while cognitive distraction reduces the overall impairments of distraction on driver performance. Therefore, it is not necessary to detect cognitive distraction if visual distraction is present.

These approaches to detecting distraction can be also generalized to estimate other performance impairments, such as driver fatigue.

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Title and Department

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Graduate College
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Iowa City, Iowa

CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

Yulan Liang

has been approved by the Examining Committee
for the thesis requirement for the Doctor of Philosophy
degree in Industrial Engineering at the May 2009 graduation.

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Geb W. Thomas

To my parents and my husband

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CHAPTER I. INTRODUCTION

Driving is a common activity for many people, making driving safety an important issue in everyday life. Over the 20 years from 1980 to 2000, the number of licensed drivers in the U.S. increased 23.7%, from about 154.0 million to 190.6 million. Total annual mileage traveled annually in the U.S. increased 28.9% from 1990 to 2000 and reached 2,767 billion miles in 2000 (USDOT, 2000). Despite of safety improvements in road and vehicle design, the total number of fatal crashes still increases. Motor vehicle-related fatalities increased from 33,186 in 1950 to 42,387 in 2000, while the rate per 100 million miles decreased from 7.24 to 1.53 (Wang, Knipling, & Goodman, 1995). The increasing number of fatalities demonstrates that driving safety represents a persistent and important issue. Reducing crash involvement would benefit millions of people across the world.

Although most motor-vehicle crashes are attributed to multiple causes, driver error represents a dominant one because drivers are responsible for operating vehicles and avoiding crashes (Lee, 2006). Compared to 34.9% for roadway factors and 9.1% for vehicle factors, driver errors contribute to 92.9% of crashes (Treat et al., 1977). For example, rear-end collisions that comprise approximately 30% of all crashes and roadway departure crashes, which cause the greatest number of fatalities have been largely attributed to the inability of drivers to detect hazards and control the vehicle properly (The National Safety Council, 1996).

Most of these performance breakdowns result from the impairments of driver's attention. Four major categories of attentional impairments include alcohol, fatigue, aging, and distraction. Alcohol contributes to approximately 40% of fatalities in US highway (Lee, 2006). Fatigue is often cited in the accidents involving young drivers and truck drivers because these drivers tend to adopt risky strategies to drive at night and/or lack good-quality sleep (Lee, 2006). Aging results in longer response time to hazards and more narrow field of attention in old drivers (Ball & Owsley, 1993; Owsley et al., 1998).

Compared with the above three impairments, distraction, the fourth impairment, is the impairment that has become increasingly important with the introduction of in-vehicle technology (e.g., navigation systems, cell phones, and internet) and has drawn increasing attention from human factor researchers and policy makers in the area of transportation safety. Driver distraction diverts driver's attention away from the activities critical for safe driving toward a competing activity (Lee, Young, & Regan, 2008). It contributes to 13-50% of all crashes, resulting in as many as 10,000 fatalities and $40 billion in damages each year (Lee, 2006). In the 100-Car Study, driver inattention contributed to nearly 80% of the crashes and 65% of the near-crashes (Klauer, Neale, Dingus, Ramsey, & Sudweeks, 2005). The trend toward increasing use of in-vehicle information systems (IVISs) is critical because IVISs induce distraction (Alm & Nilsson, 1995), which includes two major types: visual distraction and cognitive distraction. Visual distraction can be described as "eye-off-road", and cognitive distraction as "mind-off-road" (Victor, 2005). Both types of distraction can lead to larger lane variation, more abrupt steering control, slower response to hazards, and less efficient visual perception than attentive driving. Moreover, these two types of distraction can occur in combination and interact with each other.

A promising strategy to minimize driver distraction is to develop adaptive distraction mitigation systems, which adjust their functions and provide assistance to reduce distraction based on the state of drivers. These systems build on the concept of cooperative automation, which includes identifying the user's state and adapting to it. Figure 1 depicts an adaptive system to mitigate driver distraction. The system assesses driver state based on the information collected by a range of sensors in real time and provides the driver with mitigation strategies to maintain acceptable performance. The mitigation strategies in such an adaptive system include warning drivers, blocking distraction sources, and/or providing feedback. For example, the SAVE-IT (SAfety VEhicle using adaptive Interface Technology) project developed a vehicle incorporating adaptive interface technology to mitigate driver distraction and evaluated its safety benefits (Witt, 2003).

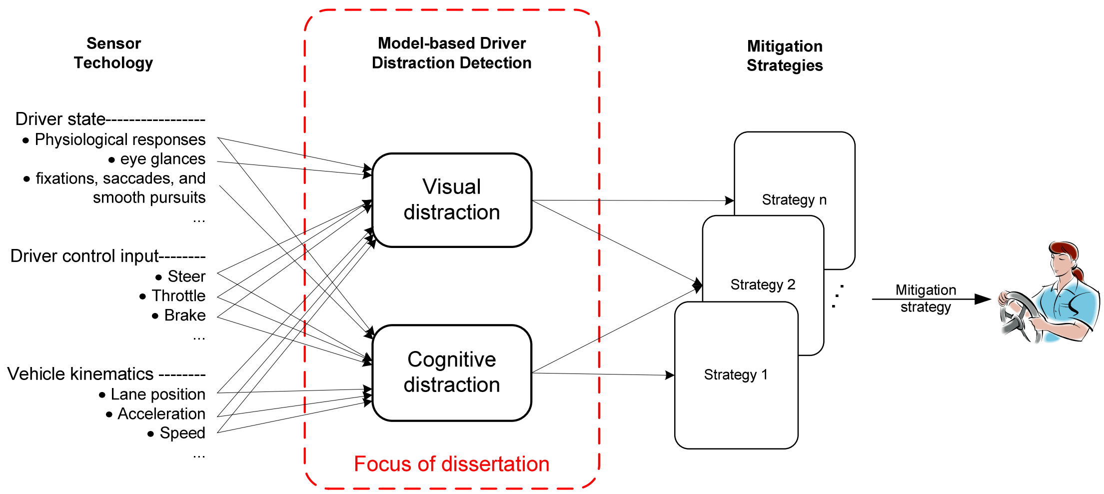

Figure 1. The structure of distraction mitigation systems. The arrows indicate data/information flow.

Accurately identifying distraction in real time is a critical challenge in developing adaptive mitigation systems. However, the algorithms to detect distraction have not been well developed. To address this need, the goal of this dissertation is to develop detection algorithms for visual distraction, cognitive distraction, and the combination of two in real time. The contributions of this dissertation include 1) applying data mining and other quantitative methods to detect driver distraction, and 2) investigating how visual distraction and cognitive distraction interact to influence driver performance.

CHAPTER II. BACKGROUND

This section summarizes the literature related to real-time detection of driver distraction, including the research on cooperative automation, driver distraction, and detection techniques. A review of cooperative automation, including adaptive automation and augmented cognition, highlights the need for such systems and identifies a major challenge for driver distraction mitigation systems—detecting driver distraction. This is the focus of this dissertation. Detecting driver distraction requires clear understanding of how two major types of distraction, visual and cognitive, affect driver behavior because their characteristics determine how to implement the detection. Moreover, depending on secondary task characteristics visual and cognitive distraction often occurs in combination, and their effects might interact. Therefore, detecting visual, cognitive, and combined distraction is critical. A summary of existing approaches shows that data mining methods represent an innovative and promising way to detect cognitive distraction. In contrast, visual distraction can be estimated using models of visual scanning behavior that are associated with increased crash risk. Based on the interaction of two types of distraction, the combined distraction may be identified by combining the detection algorithms for visual distraction and cognitive distraction in sequence. This dissertation combines multiple non-linear, time-series techniques to improve the detection of visual and cognitive distraction and develops a sequential strategy to identify the combined distraction.

Cooperative automation and its application in driving

Automation is being increasingly introduced into the vehicle to aid drivers. For example, cruise control helps drivers maintain a constant speed; collision warning systems warn drivers of impending crashes, and navigation systems (GPS) provide directions in real-time. These systems can make driving easier, safer, and more efficient (Lee, 2007). However, the benefits of these systems can be compromised because they are not adaptive to driver states and can cause or encourage distraction. Identifying and adapting to driver distraction is important in in-vehicle automation design.

Most current automation used while driving is static—the level of automation does not change across time or according to driver or roadway state (Byrne & Parasuraman, 1996). A drawback of static automation is that it can transform people from active operators to passive supervisors and disengage them from the primary task, causing a mismatch between user capability and task requirements (Scerbo, 1996). Static automation in vehicles can undermine drivers' performance by reducing situational awareness, impairing decision making, and degrading skills (Byrne & Parasuraman, 1996). One way to diminish these negative effects and promote the benefits of automation is to develop cooperative automation that adaptively adjust its functions according to user state (Hoc, 2001; Rouse, 1988).

Cooperative automation

Cooperative automation supports two-way communication between automation and the user (Figure 2). In this communication, users play a voluntary role where they can monitor the automation to decide how it should be used. Cooperative automation monitors user state and adapts its functions according to the changing user capabilities and limitations, which static automation cannot accomplish. For example, an adaptive collision warning system can adjust the timing of warnings based on whether the driver is distracted or not. Such an adaptive system can enhance safety benefits by providing earlier warnings when the driver is distracted and reducing false alarms by delaying warnings for attentive drivers. However, these benefits depend on successfully detecting driver distraction.

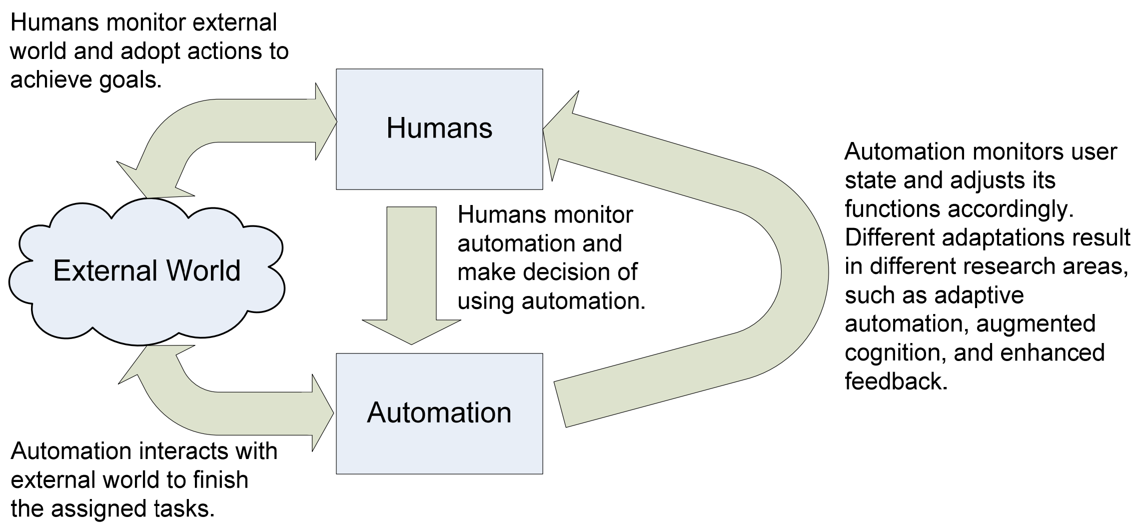

Figure 2. An overview of the relationships between human, environment, and cooperative automation.

Research areas related to cooperative automation include adaptive automation and augmented cognition. Adaptive automation promotes performance by dynamically assigning tasks to either the human or the automation based on task demand, human capability, and system requirements (Byrne & Parasuraman, 1996). Task aiding, an example of adaptive automation, identifies the users' need for additional support associated with increased workload and provides assistance to help users maintain acceptable performance (Rouse, 1988). Identification of users' needs is critical issue for task aiding, which can be implemented by requiring users to report their needs or detecting users' needs from their performance. Multiple studies have demonstrated that task aiding systems can improve human performance from 2% to 40% (Rouse, 1988). A successful example was the Pilot's Associate (PA) sponsored by the Defense Advanced Research Projects Agency (DARPA), which developed a mission management system to enhance pilot situation awareness and decision making (Schmorrow & Kruse, 2004). However, PA required pilots to report their intent explicitly. This approach to identifying operator state is infeasible in driving because of high training demands and distraction caused by such interactions.

Augmented cognition applies the knowledge from sensor technology, neurophysiological measurement, computer science, and cognitive engineering to extend human information processing and decision making capabilities (Schmorrow & Kruse, 2004). Augmented cognition focuses on the efficiency of information delivery between the user, system, and other users. As an example, a system records electroencephalography (EEG) data and gaze activity from the user to assess workload in real time (Singer, 2005). The system also recognizes user intent from his/her conversations with other users. Based on this unobtrusively obtained information, the system highlights messages that match the user's interest to enhance decision making and reduce workload. Some real systems built upon augmented cognition include Attentional User Interface (AUI) by Microsoft Research (Schmorrow & Kruse, 2004), Technical Integration Experiment (TIE) by DARPA (Schmorrow & McBride, 2004; St John, Kobus, Morrison, & Schmorrow, 2004), and "attention assist" system by Mercedes-Benz™.

For adaptive automation and augmented cognition, it is critical to correctly assess user state (Schmorrow & Kruse, 2004). Only with this information can cooperative automation benefit users—for adaptive automation to manage the level of automation and for augmented cognitive to mediate the information from the system or other users to enhance performance. Cooperative automation is being developed for many applications, but in-vehicle systems are the particular focus of this dissertation. Cooperative automation promises enhance driving safety, particularly by mitigating driver distraction.

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Driver distraction mitigation systems

Recent research projects, such as HASTE and AIDE in Europe (Carsten et al., 2005) and SAVE-IT in U.S. (Witt, 2003), have attempted to identify predictors of driver distraction and to develop in-vehicle systems that adapt to driver state and mitigate distraction. The HASTE (Human machine interface And the Safety of Traffic in Europe) program examined driver performance under different levels of workload to identify potential predictors of driver distraction. The results showed that vehicle lateral control could be used to identify visual distraction, but no single measure could identify cognitive distraction. The study proposed using event detection to evaluate cognitive load of in-vehicle information systems (IVISs). However, because this task is highly intrusive it is not suitable for assessing drivers' cognitive state in real-time systems. The AIDE (Adaptive Integrated Driver-vehicle interfacE) program studied how adaptive technologies could be used to integrate different in-vehicle support systems. The program focused on 1) modeling relationships between drivers, vehicles, and environment, 2) investigating driver adaptation to in-vehicle support systems, 3) creating guidelines and technology for IVIS design, and 4) evaluating the risk of using these systems. However, like the HASTE program, the AIDE program was unable to provide unobtrusive and real-time measures for assessing driver cognitive load.

The National Highway Traffic Safety Administration (NHTSA) sponsored SAVE-IT (SAfety VEhicle using adaptive Interface Technology) to develop a test vehicle that incorporated an adaptive interface designed to mitigate distraction (Witt, 2003). One part of the project focused on creating a system that inferred driver state from sensor data. The research focused on 1) identifying distraction-related driving scenarios, 2) developing and evaluating technologies to assess driver distraction, driver performance, driver intent, and task demand, and 3) generating rules to prioritize in-vehicle information to adapt information presentation based on the state of the driver. This program identified possible safety benefits of adaptive in-vehicle systems and the requirements necessary to achieve those benefits. It also helped create a basis for the industry standards needed to achieve widespread application of a common adaptive interface.

The driver distraction mitigation system developed in the SAVE-IT program sought to diminish overload caused by drivers engaging in distracting tasks and to guide driver behavior to maintain safety (Figure 3). Once detected, driver distraction can be mitigated with a range of strategies including adapting collision warnings, redirecting attention, and post-drive feedback (Donmez, Boyle, & Lee, 2003). These strategies depend on correctly identifying when the driver is distracted, which is the focus of this dissertation.

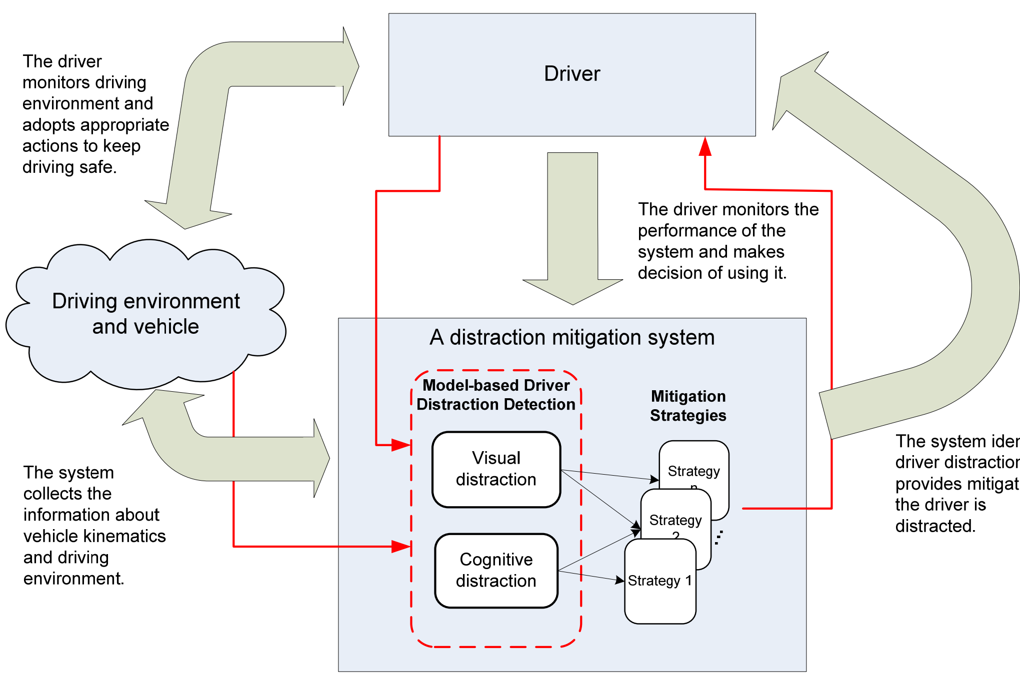


Figure 3. A distraction detection in the context of cooperative automation.

The effects of driver distraction

One challenge of detecting driver distraction is its diversity. Although a variety of ways can be used to discriminate distraction types, one useful approach is to differentiate the attentional resources for which the driving and secondary tasks compete. Multiple resource theory (MRT), a well-respected approach to describe dual-task performance, can be used to identify the major types of distraction and describe their effects (Wickens, 2002). The attentional resources outlined by this theory can define the major types of distraction.

Multiple Resource Theory (MRT)

Multiple resource theory (MRT) describes dual task performance in terms of competing attentional resources defined by four dimensions: 1) processing stage differentiating perception and response, 2) processing code differentiating the process of analogue/spatial or categorical/verbal information, 3) perceptual modalities differentiating visual and auditory (Wickens, 2002), and 4) visual channel differentiating focal or ambient vision (Horrey & Wickens, 2004a). When two tasks compete for the same resource one or both of the tasks degrades. Driving places major demands on resources associated with visual perception, spatially-coded working memory, and motor response, but minor demands on auditory perception and verbally coded-working memory, or verbal response. According to MRT, secondary tasks that compete for the same resources as driving will degrade driving performance. All tasks require some degree of central processing. Consequently, even secondary tasks that do not directly compete for the resources important for driving will degrade driving performance.

Many types of distraction can be defined using the dimensions of MRT. However, based on the consequences and likelihood of resource competition between driving and secondary tasks, this dissertation focuses on two types of distraction: visual distraction and cognitive distraction. Visual distraction occurs when drivers look away from the roadway (e.g., to adjust a radio), reflecting the substantial role of visual attention in driving. Cognitive distraction reflects the shared central processing demand of driving and secondary tasks. This distraction disrupts the allocation of visual attention to the driving scene and the ability to process information being attended to (Recarte & Nunes, 2003; Strayer, Drews, & Johnston, 2003; Victor, Harbluk, & Engström, 2005). We can describe visual distraction as "eye-off-road" and cognitive distraction as "mind-off-road" (Victor, 2005). The major difference between two types of distraction is how they influence drivers' visual attention, with visual distraction having a clear and observable effect and cognitive distraction having a subtle influence on the distribution of attention and consolidation of attended information.

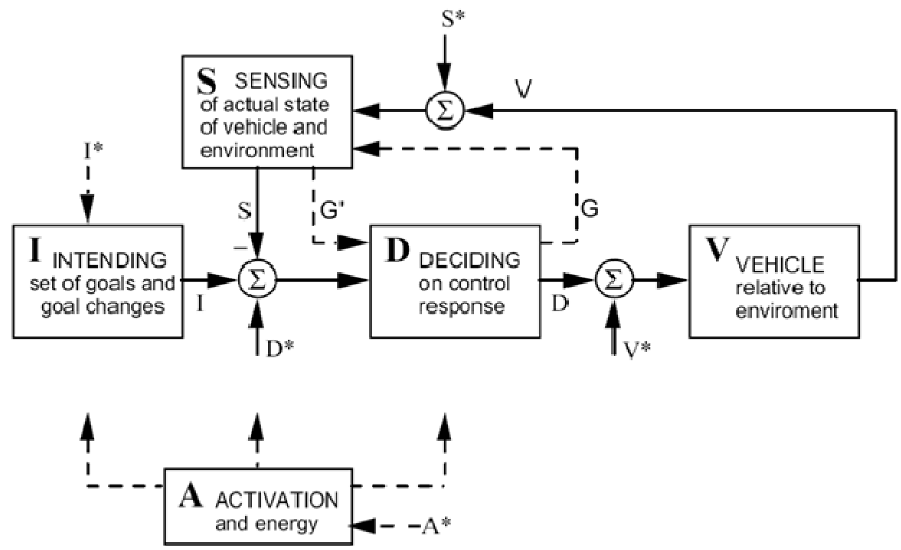
Visual channels can be divided into focal vision and ambient vision, which contribute differently to driving. Focal vision is situated within 20-30 degrees of the central visual field (Horrey & Wickens, 2004b). It provides high visual acuity to support precise judgments and is typically guided by conscious intention. Ambient vision can encompass 180 degrees in the horizontal direction and 40 degrees in the vertical direction. It supports subconscious activity, and is used to identify spatial orientation and to sense motion. During driving, drivers direct focal vision around the driving scene to perceive the roadway and detect hazardous events. Ambient vision is sensitive to the motion in the peripheral area and plays an important role in vehicle control, such as lane keeping. Visual distraction diverts focal vision from the road and the driver's ability to detect hazards is severely diminished. Nonetheless, drivers can perceive the outline of the roadway and their motion relative to the roadway through ambient vision so that they still can have acceptable, but degraded, lane keeping performance (Horrey & Wickens, 2004a). Cognitive distraction does not directly interfere with focal vision and is therefore less disruptive to hazard detection and vehicle control compared to visual distraction.

Besides passively responding to the demands of secondary tasks, drivers, as active controllers, decide what tasks to perform and when they perform them and so they coordinate their behavior based on the driving context. This ability to adapt mediates how the competition for attentional resources undermines driving safety. Task engagement, another theoretical dimension, considers the driver as active controllers who manage secondary task involvement and driving demands.

Task engagement and driver adaption

Task engagement describes how drivers actively distribute their attention between driving and secondary tasks based on internal safety criteria and task characteristics. The internal safety criteria used by a driver can change over time and are determined by multiple factors including the emerging roadway situation, the importance of the task, and the driver's memory and experience. Visual distraction and cognitive distraction produce different profiles of task engagement according to how drivers evaluate the detrimental effects of the distractions on safety.

Sheridan (2004) proposed a control-theory approach that can describe driver adaptation under distraction (Figure 4). The model describes distraction as disturbance of the driving task. In Figure 4, S* represents sensing interference to driving and can model visual distraction; D* represents cognitive interference that undermines decision making and judgment and can model cognitive distraction. In this model, drivers' adaptation is represented by some criteria, according to which drivers switch between driving and secondary tasks when these two tasks compete for the same resources. When the switch occurs, drivers direct the resources that are shared by two tasks to one task and hold the last input of the other task. For example, a driver will look back to the road when s/he looks away from the road for two seconds. The switching criteria depend on many factors, such as driving demands, environmental conditions, and even the confidence of drivers to their skills. Therefore, understanding drivers' switching behavior in different situations is central to explaining drivers' when and how drivers engage in secondary tasks. Such switching behavior is central to the process of visual sampling associated with monitoring the road and performing a secondary task.



Blocks (I, S, and D), regular, and with* represent input-output transfer functions of the active human driver, corresponding output, and corresponding disturbance (distraction) variables. The output V of the vehicle (relative to the environment) and V* are the system state and the disturbance to the vehicle. G and G′ represent the secondary motor loop necessary to control sensor orientation. The block A represents the human body's mechanisms to effect activation (alertness, energy) with corresponding disturbance A*.

Figure 4. A control system for safe driving (Sheridan, 2004)

Adaptive behavior in visual sampling

Drivers adapt to visual distraction by intermittently sampling visual information from the roadway. One study described this behavior using an uncertainty model (Senders, Kristofferson, Levison, Dietrich, & Ward, 1967). When drivers look away from the road, the uncertainty about the roadway situation accumulates because of information obsolescence and loss (Senders et al., 1967). When uncertainty reaches a certain fixed threshold, drivers look back to the road. The study found that when drivers' sampling of the road was limited, drivers tended to drive more slowly to limit uncertainty. A more recent model, built upon Senders' work, directly described the switching criteria in terms of the duration of off-road glances (Wierwille, 1993). According to the model, drivers look back to the road when off-road glances last 1.8 seconds on straight road and 1.2 seconds on curved road.

Senders' and Wierwille's models simulate task disengagement behavior of drivers using simple rules (i.e., uncertainty threshold and time threshold of off-road glances). Nonetheless, the decision of drivers to engage in a secondary task while driving may be more complex. As shown in Figure 5, the demand of IVIS tasks, the real-time driving situation, driver attitudes regarding task priority and their skills, and perceived risk all contribute to this decision. Task complexity, visual angle between the secondary task and the driving scene (Horrey & Wickens, 2004a), and requirement for manual operation (Dingus, Antin, Hulse, & Wirewille, 1989) can determine the demand of an in-vehicle task. The evolving driving situation (e.g., traffic, road surface condition, weather, and lighting) determines the dynamic demands of the driving task. In-vehicle task demand and driving demand represent objective requirements, whereas drivers' attitudes and perceived risk represent subjective factors that differ between drivers and across time.

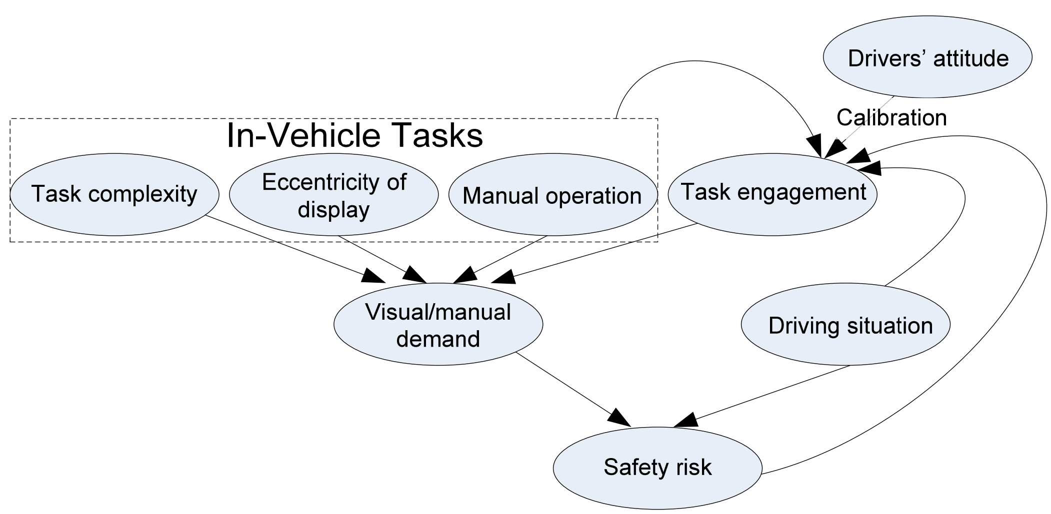


Figure 5. Multiple factors affect task engagement during visual distraction.

These factors interact to affect driver disengagement behavior. Horrey et al. (2006) applied a model to calculate the likelihood of drivers allocating visual attention between driving and IVIS based on four characteristics (SEEV) of the tasks: Salience, Effort, Expectation, and Value. Salience characterizes the conspicuity of the information related to the tasks. Effort describes the difficulty of scanning the information and can be manipulated by the visual angle across which people have to move their eyes to see the information. Expectation describes the driver's opinion regarding the update rate of the information and is expressed by the bandwidth of the information. Value is expressed by the relevance and priority of the information. A model based on SEEV predicted approximately 95% of the variance in scanning behavior. Compared with the simple rules (Senders et al., 1967; Wierwille, 1993), a more complex model, like SEEV, can integrate more factors that may influence the adaptation of drivers.

Adaptive behavior in managing cognitive demand

Although the engagement of driver's mind in either driving or secondary tasks cannot be directly observed, some evidence shows that drivers adjust their behavior according to cognitive demand of secondary tasks. Drivers tend to increase the distance to the leading vehicle in the car-following scenario when they engage in cognitively demanding secondary tasks (Horrey & Simons, 2007; Strayer & Drews, 2004; Strayer et al., 2003), suggesting that drivers may compensate for the impairments that secondary tasks impose.

However, this adaptive behavior may not compensate for the full range of demands in a dynamic situation. Horrey and Simons (2007) examined how drivers adapt to cognitive workload when passing a vehicle or following a leading vehicle. Unlike the car-following scenario, drivers did not increase their safety margin under high cognitive workload when passing a vehicle. One explanation is that the cognitive distraction diminishes the driver's capacity to adapt their behavior to changing workload, especially when workload is already high and tasks are time constrained. Overtaking may have higher demand than car following, and therefore drivers may have less capacity to adapt during overtaking. One study found that drivers drove faster than the normal when distracted by a cognitive task (Liu, 2001). This suggests that drivers may fail to appropriately adapt to compensate for secondary cognitive demands. Adaptive driving support systems may be particularly useful at helping drivers manage cognitive workload effectively.

The MRT and task engagement together can provide a comprehensive overview of how distraction affects driver behavior, which is the foundation of detecting driver distraction. The following will summarize the individual and joint effects of visual distraction and cognitive distraction on driver behavior.

Visual distraction

Visual distraction degrades driving performance and hazard perception. During the distraction, drivers tend to move the steering wheel abruptly, have large lane variability, and miss/respond slowly to safety-critical events (Donmez, Boyle, & Lee, 2007; Zhang, Smith, & Witt, 2006). At the same time, drivers often notice degraded performance and adapt their behavior (e.g., reducing speed) to compensate for the effects of visual distraction (Engström, Johansson, & Ostlund, 2005; Senders et al., 1967). These performance decrements are all highly correlated with drivers' off-road eye glance patterns (Dingus et al., 1989; Dingus, Hulse, McGehee, & Manakkal, 1994; Donmez et al., 2007; Sodhi, Reimer, & Llamazares, 2002; Zhang et al., 2006). For example, driver visual attention alternates between the roadway and in-vehicle interface during the distraction, as shown in Figure 6c. Frequent, long off-road glances are especially detrimental (Wierwille & Tijerina, 1998). During off-road glances, drivers gradually lose awareness of the driving situation. This effect can be directly assessed using the drivers' eye glance patterns.

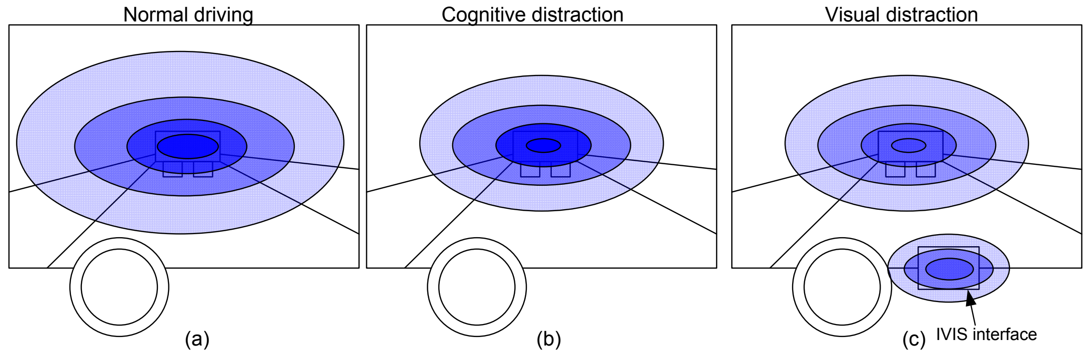


Figure 6. An illustration of gaze distribution in (a) normal driving, (b) cognitive distraction, and (c) visual distraction. The shading level presents gaze density.

Cognitive distraction

Cognitive distraction degrades driving performance and hazard perception, but with less serious and consistent manner compared to visual distraction (Table 1). A meta-analysis of 23 studies found that cognitive distraction caused by using auditory e-mail systems, performing math calculation, or holding hand-free cell phone conversations delayed driver response to hazards by an average of 130 ms (Horrey & Wickens, 2006). For example, drivers reacted more slowly to lead vehicle braking events (Lamble, Kauranen, Laakso, & Summala, 1999; Lee, Caven, Haake, & Brown, 2001) and missed more traffic signals (Strayer et al., 2003; Strayer & Johnston, 2001) when they performed cognitively distracting tasks while driving. However, Blanco and her colleagues (2006) found that only in-vehicle tasks with more than one decision-making element had a substantial negative impact on drivers' performance.

Cognitive distraction diverts central information processing resources from driving and is associated with two general effects. First, cognitive distraction can undermine the process of consolidating attended information. Cognitive distraction, associated with cell phone conversations, impairs implicit perceptual memory and explicit memory in recognizing items in the road environment (Strayer et al., 2003;

Strayer & Johnston, 2001). These results suggest that some visual information is not being processed effectively when drivers are cognitively distracted leading to impaired performance in detecting targets across the entire visual scene (Recarte & Nunes, 2000, 2003).

Cognitive distraction also changes the pattern of spatial and temporal eye gaze distribution (Recarte & Nunes, 2000, 2003). Increased cognitive load is associated with longer fixations, gaze concentration, and less frequent glances to the mirrors and speedometer (Recarte & Nunes, 2000) (Table 1). Figure 6b illustrates the typical change in gaze distribution during cognitive distraction. The gaze tends to concentrate more densely in the center of the driving scene and the area scanned shrinks compared to the normal driving. This gaze concentration may reflect competition for attentional resources between the cognitive demands of the secondary task and the guidance of eye movements. Nonetheless, this gaze concentration was not found all studies (Reyes & Lee, 2008), implying that there may not be a single measure that can assess cognitive distraction (Engström et al., 2005).

Unlike visual distraction, cognitive distraction may also undermine drivers' ability to adapt to secondary task demands. Drivers may fail to adapt appropriately under cognitive distraction and may remain engaged in secondary tasks even when driving demand increases (Horrey & Simons, 2007; Liu, 2001). Adaptive driving support systems may be particularly useful at helping drivers to manage cognitive workload effectively.

Combined distraction

Visual distraction and cognitive distraction often occur simultaneously in real driving, and their combined effects have not been systematically examined. This section compares the effects of visual and cognitive distraction and examines how the combined demands of visual and cognitive tasks affect driver behavior.

Visual distraction and cognitive distraction have different effects on driver behavior. CAMP (Crash Avoidance Metrics Partnership) and HASTE attempted to develop performance metrics and methodologies to assess distraction (L. Angell et al., 2006; Carsten et al., 2005). Both programs found that the effects of visual distraction are salient and consistent—increased distraction leads to significantly degraded lateral control. In contrast, cognitive distraction effects are subtle and diverse. Relative to visual distraction, cognitive distraction accounts for much less of the overall variance in driving performance.

This difference can be explained using MRT. Visual distraction interferes with the driving task more than cognitive distraction because visual attention is a crucial resource for driving. That is, visual distraction directly interferes with visual attention to the roadway. During off-road glances, drivers lose awareness of the driving context, which can seriously undermine hazard detection, and lateral and longitudinal vehicle control. Cognitive distraction disrupts, but does not totally block, information processing of the roadway situation. Even with cognitive demands of secondary tasks, drivers still have resources to process roadway information. Therefore, visual distraction tends to impose more serious and consistent impairments on driving performance than cognitive distraction (L. Angell et al., 2006).

Table 1 summarizes the effects of visual distraction and cognitive distraction on driver behavior. The two types of distraction show opposite effects on the variability of gaze distribution (Figure 6). First, visual distraction results in a large variability of gaze distribution (Dingus et al., 1997; Donmez et al., 2007; Liu, 2001), while cognitive distraction causes gaze concentration and result in a low frequency of glances to mirrors (Recarte & Nunes, 2003; Victor et al., 2005). Second, the two types of distractions cause different patterns of steering correction and lane keeping. During visual distraction, the intermittent attention to the roadway results in large, discrete steering adjustments (Engström et al., 2005), and this steering pattern generates large lane variation.

Cognitive distraction does not divert visual attention from the road and results in more frequent, smaller steering corrections than visual distraction (Engström et al., 2005), leading to improved lane maintenance. Steering error in Table 1 measures the smoothness of steering control and is calculated by the difference between the actual steering wheel movements and the predicted movements based on a Taylor series extrapolation of previous steering movements (Nakayama, Futami, Nakamura, & Boer, 1999). Higher values of steering error indicate more abrupt steering control.

Table 1. Effects of distraction on driver behavior: visual, cognitive, and combined

	Visual distraction	**Cognitive distraction**	**Combined distraction (hypothesized)**
Eye movement	High frequency of off-road glances, long total eye-off-road time, and low percentage of gaze to the center of the road	Gaze concentration in the center of the road	High frequency of off-road glances and longer total eye-off-road time, gaze concentration when drivers look at the road
Lane position	Large lane variation	Unchanged or small lane variation	Large lane variation
Steering control	Discrete steering correction and large correction magnitude (>5°, large steering error)	Small correction magnitude (< 3°, small steering error)	Discrete steering correction and both large and small correction magnitude (>5°)

Visual distraction and cognitive distraction also have different effects on the ability of drivers to adapt. During visual distraction drivers are more aware of the increased workload and actively adjust their behavior, such reducing speed (Senders et al., 1967). With cognitive distraction, drivers may not be aware of the degree of distraction, especially in a dynamic situation. Drivers may drive faster than normal

(Engström et al., 2005; Liu, 2001) or may not increase their safety margin to compensate for the impairment caused by cognitive tasks (Horrey & Simons, 2007).

In the real driving environment, IVIS often confront drivers with a combination of visual and cognitive demands. For example, entering an address into a navigation system involves visual demands to enter information and select menu options from a touch screen and cognitive demands to recall the address and make route decisions. In this situation, visual distraction and cognitive distraction interact to effect driver behavior. The extent of the interaction between visual distraction and cognitive distraction likely varies based on task characteristics. In one extreme the effects of two types of distraction may counteract each other; in the other extreme the combined effect may be larger than or equal to the sum of the two types of distraction. Preliminary evidence shows that cognitive and visual distractions combine in an additive manner (Lee, Lee, & Boyle, 2007).

The MRT and task engagement can help to identify the interaction of visual distraction and cognitive distraction. From the MRT perspective, visual demand diverts visual attention away from the roadway; whereas cognitive demand disrupts information processing. The conflicting demands are most pronounced for visual demand and so impairments associated with visual demand may dominate. From the perspective of driver adaptation and control of task engagement, the cognitive component may undermine the drivers' ability to manage secondary and driving tasks under combined distraction, which results in prolonged secondary task engagement. Based on the two theoretical dimensions, visual distraction is more likely to dominate the effects of combined distraction and cognitive distraction may reinforce this impairment by undermining the drivers' ability to adapt. Therefore, combined distraction may result in longer off-road glances, larger variability of lane position, and more abrupt steering than either visual or cognitive distraction alone. The most right column in Table 1 presents hypothesized effects of combined distraction on driver behavior.

Although drivers can avoid many of the conflicts predicted by the MRT by disengaging from a secondary task, their adaptation is often incomplete. Adaptive systems may enhance drivers ability to adapt, but must detect distraction accurately. Because visual, cognitive, and combined distraction do not affect driver behavior in the same way, detection should be tailored to the characteristics of each type of distraction.

Detection and estimation of driver distraction

This section discusses several important considerations in developing detection of driver distraction, including distraction indicators and associated time constants, detection algorithms, and individual differences. The decisions about these factors are all influenced by the characteristics of the type of distraction. In this dissertation, estimation refers to quantifying the level of distraction and detection refers to identifying the existence of distraction.

Indicators and time constant of driver distraction

The choice of indicators and time constant to detect distraction depends on how distraction influences driver behavior and how fast these effects can be reflected in the performance measures. Visual distraction occurs when drivers look away from the roadway and can be directly indicated by the drivers' eye glance patterns. Duration, history, and eccentricity of eye glances can indicate the level of visual distraction (Donmez et al., 2007; Engström & Mårdh, 2007; Senders et al., 1967). Moreover, the effects of off-road glances can be reflected in driver behavior immediately or within a very short period of time. Considering momentary changes or changes that occur across a short time period for driver eye glance patterns is appropriate for detecting visual distraction.

Unlike visual distraction, cognitive distraction results in subtle, inconsistent, and relatively extended effects on driver behavior. Although there is no overt indicator for cognitive distraction it may be feasible to identify cognitive distraction from multiple performance measures across a relatively long period of time. Commonly used driving performance measures include lane position and steering variability. Unfortunately, driving performance often reflects consequences of distraction, and it may be too late to mitigate distraction when degradation in driving performance occurs. Incorporating eye movement measures that have a close relationship with driver attention may help identify distraction before it undermines safety. Long periods of time (e.g., 30 seconds) represent and appropriate time constant because they have been shown to produce better detection algorithms for cognitive distraction (Liang, Reyes, & Lee, 2007).

Fixations, saccades, and smooth pursuits represent three types of eye movements can be used to help identify cognitive distraction. Fixations occur when an observer's eyes are nearly stationary. The fixation position and duration may relate to attention orientation and the amount of information perceived from the fixated location, respectively (Hayhoe, 2004). Saccades are very fast movements that occur when the eyes move from one point of fixation to another. Smooth pursuits occur when the observer tracks a moving object, such as a passing vehicle. They serve to stabilize an object on the retina so that visual information can be perceived while the object is moving relative to the observer. In the context of driving, smooth pursuits have a particularly important function; they capture information from the dynamic driving scene. Both fixations and smooth pursuit movements may reflect the how cognitive distraction interferes with how drivers acquire visual information.

Several studies have shown links between eye movements and cognitive load (Hayhoe, 2004). Cognitive load can be indicated by saccade distance, which decreases as tasks become increasingly complex (May, Kennedy, Williams, Dunlap, & Brannan, 1990). Rantanen and Goldberg (1999) found that the visual field shrank 7.8% during a moderate-workload counting task and 13.6% during a cognitively demanding counting task. Similarly, increased cognitive demand during driving decreased spatial gaze variability by 16-70%, as defined by the area covered by one standard deviation of gaze location in both the horizontal and vertical directions (Recarte & Nunes, 2000, 2003). These links between eye movement and cognitive load show that eye movement measures are good candidates to predict cognitive distraction. Different characteristics of visual and cognitive distractions lead to different indicators and time constant, implying that detection of types of distraction requires implementing different techniques.

Algorithms for detecting distraction

Driver distraction detection systems must integrate the data from multiple sources. One way to address this need is to construct a data fusion system to integrate data from multiple sources, align data sets, correlate related variables, and combine them to support detection or classification decisions (Waltz, 1998). A benefit of using data fusion is that such a system is typically structured in a hierarchical form and can integrate information at different levels of abstraction. For example, the system can aggregate sensor data to measures driver performance at the most concrete level and use these measures to infer driver state at a higher level. This hierarchical structure of data can logically organize data and inferences to reduce the parameter space of the detection procedure. Moreover, the data fusion system can continuously refine estimates at different hierarchical levels independently to support real-time detection.

Two general approaches can be used to implement data fusion systems for detecting driver distraction: top-down and bottom-up. The top-down approaches, such as the Multiple Resource Theory (Wickens, 2002), ACT-R (Salvucci & Macuga, 2002), and control theory (Sheridan, 2004), identify driver state based on known characteristics and mechanisms of driver behavior. Examples of top-down models include an ACT-R model that predicted driver behavior when drivers used different types of cell phone dialing systems (Salvucci, 2001) and a control-theory model of driver distraction that considered distraction as a disturbance to driving (Sheridan, 2004). These models only captured the trend of several performance measures, and not the changes of all measures that might be available for driver state estimation. More critically, such approaches require an accurate model of driver behavior, which is often difficult to develop. The theoretical basis of these models may not be complete enough to describe complex human behaviors such as driving under cognitive distraction. The limitation of the top-down approach is that it depends on a thorough knowledge of the underlying mechanisms of distraction-related impairment, which is currently lacking.

A bottom-up approach overcomes this limitation by applying data mining methods to extract relationships between performance indicators and driver state from data rather than from theories of cognition. Data mining includes a broad range of algorithms that can search large volumes of data for unknown patterns. Examples of data mining techniques include regression, decision trees, clustering, Support Vector Machines (SVMs), and Bayesian Networks (BNs). These techniques are based on contributions from multiple disciplines (e.g., statistics, information retrieval, machine learning, and pattern recognition) and have been successfully applied in business and health care (Baldi & Brunak, 2001; Tan, 2005). In the detection of distraction, SVM, and BNs have been successfully used to identify driver cognitive distraction (Liang & Lee, 2008; Liang, Lee, & Reyes, 2007; Liang, Reyes et al., 2007).

Data fusion systems can be constructed with three strategies: top-down approach, bottom-up approach, or an approach that combines elements of top-down and bottom-up strategies. The choice of the strategy depends on the availability of domain knowledge, as shown in Table 2. When the relationship between the data and the states to be estimated are well understood, data fusion systems can be constructed using a top-down approach. Many current data fusion systems use this strategy (Llinas & Hall, 1998). Nevertheless, incomplete domain knowledge presents an important constraint of using only a top-down strategy, such as in the detection of driver distraction. The bottom-up and combined strategies overcome this limitation. The combined strategy is particularly promising because it can integrate domain knowledge to guide the training of data mining algorithms and may be the best strategy to detect driver distraction. Oliver and Horvitz (2005) demonstrated the effectiveness of the combined strategy in recognizing office activities from sound and video data using Hidden Markov Models (HMMs) and Dynamic Bayesian Networks (DBNs).

Table 2. Matrix of data fusion strategies and the availability of domain knowledge

		Data fusion strategies		
		Top-down approach	Bottom-up approach	Combined approach
Domain knowledge	Available	√	√	√
	Partially available	–	√	√
	Not available	–	√	–

For detecting distraction, the salience and consistency of visual distraction suggest that some simple and straightforward algorithms may be efficient and that the top-down or combined strategy is suitable. Cognitive distraction may depend on more complex techniques and integrate more indicators, which requires a bottom-up strategy.

Individual differences

Individual differences are an important consideration when building detection algorithms for different drivers. Driving data contains two sources of variation: one is within a driver, called intra-difference; another is between drivers, called inter-difference. The intra-difference occurs when a driver exhibits different driving behaviors under different circumstances, such as attentive driving and distracted driving, and the inter-difference refers to different styles of driving. Identifying the intra-difference between attentive driving and distracted driving is the focus of this dissertation, and the inter-difference is treated as noise and controlled for.

For visual distraction, the tendency of drivers to look at or away from the roadway presents an obvious and consistent indicator between attentive and distracted driving. Figure 7a shows that the difference between the visual distraction states likely goes beyond different driving styles of drivers, meaning that a general detection model may be suitable for all drivers. In contrast, cognitive distraction presents subtle, inconsistent effects on driver behavior. Some studies on cognitive distraction have even obtained contradictory results. For example, gaze concentration was found in some studies (Recarte & Nunes, 2000, 2003) , but not in others (Reyes & Lee, 2008). Therefore, using a general detection model for all drivers may bury intra-differences caused by cognitive distraction into the inter-difference between drivers (Figure 7b). Building an individual model for each driver represents a promising approach to detect cognitive distraction.

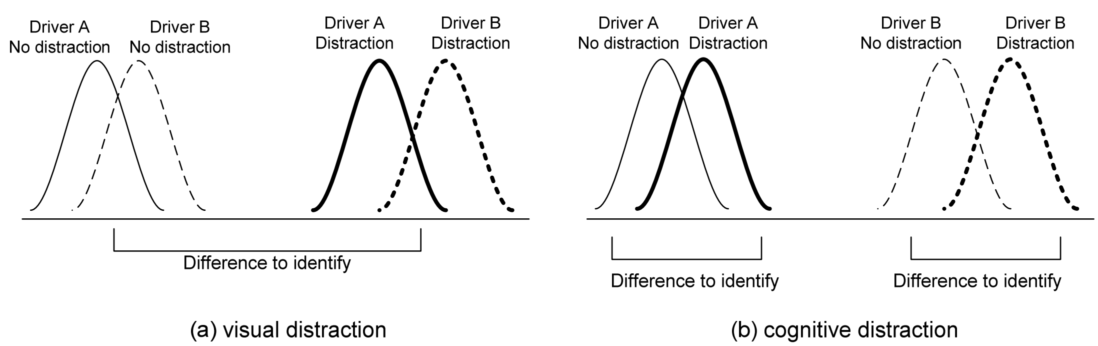


Figure 7. The illustration of behavior variation between individual drivers and between different distraction states. The distribution curves present the behavior of a certain driver under a certain distraction state.

Estimation of visual distraction

Estimation of visual distraction predicts continuously changing states of the distraction that relate to whether the driver is looking away from the roadway. The effects of visual distraction suggest that the estimation algorithms should consider the immediate changes of drivers' eye glance patterns or the changes across a relatively short time. A general algorithm can be constructed to estimate visual distraction using the top-down approach because the effects of off-road glances on driver behavior are obvious and consistent across different drivers.

Several researchers have created predictive models to quantify the risks associated with visual distraction using driver glance behavior (Donmez, Boyle, Lee, & Scott, 2006; Zhang et al., 2006). The accelerator release reaction time, the time the lead vehicle brakes until the time the driver releases the accelerator, has been predicted using the percentage of off-road glances during this period by a linear equation: (accelerator release reaction time) = 1.65 + 1.58 × (percentage of off-road glances) (Zhang et al., 2006). This relationship accounted for 50% of reaction time variance.

The detection model developed by Donmez (2006) also considered driver eye glance behavior. The model used a linear function of the current off-road glances, β_1, and total time of eye-off-road, β_2, during the last three seconds to calculate the warning parameter, γ, as: $\gamma = \alpha\beta_1 + (1-\alpha)\beta_2$. γ served as a threshold value, which indicated when drivers were "too engaged" in the visual task, and α represented the weights of β_1 and β_2 on γ. Using this equation, the risky drivers having long accelerator release reaction times received more warnings per minute than non-risky drivers for a broad range of γ and α values.

Horrey (2004b) also proposed a model to predict crash risk using mean dwell duration of in-vehicle-device glances and frequency of relevant road events expressed by the product of road event rate and speed. The equation of the model is $AccRate = MDD_{ivd} \times [(ColEvent + Curve + Steer) \times Vel + Turb]$, where MDD_{ivd} represents the mean dwell duration of in-vehicle-device glances, the rate of road events are calculated using collision events, road curvature, driver steering control and speed, and perturbations. This model heuristically summarizes the contributing crash factors caused by driver visual inattention, but has not been fully validated.

For detecting visual distraction, the duration and proportion of time for off-road glances represent the most indicative predictors. Besides these, eccentricity of eye glances to the road center is another important indicator of visual demand because the effectiveness of both focal and ambient vision degrades rapidly as glance location moves away from the road center. Engström and Mårdh (2007) used the product of the length of off-road glance and eccentricity of the glance to evaluate the visual demand of IVIS designs. The pattern of eye glances can have different consequences because of different driving demand (Dingus et al., 1989). For example, driving in low traffic on a straight interstate highway leaves drivers with more spare visual capacity than in a high-demand situation, such as driving on a high-traffic urban arterial or on a curving rural road. Therefore, to increase the accuracy of the detection, the driving performance measures, such as lane deviation and steering smoothness, should be used as indicators of visual distraction.

The relationship between drivers' visual attention and performance can be far more complex than a linear model. For example, some research shows that an exponential function of off-road time can correctly assess the magnitude of visual demand of a IVIS task (Engström & Mårdh, 2007; Wierwille & Tijerina, 1998). Moreover, time-dependent relationships are also critical because human behavior is a continuously evolving phenomenon that depends on its past history. Thus, advanced statistical techniques that describe complex and time-dependent relationship can benefit the detection of visual distraction.

Detection of cognitive distraction

Detecting cognitive distraction is much more complex than visual distraction. Most current approaches detect the discrete state of cognitive distraction (classification), and do not provide a continuous measure of distraction. Detecting cognitive distraction will likely require an integration of several performance measures over relatively long period of time, and personalized for different drivers. The challenge of detecting cognitive distraction is to integrate a large number of performance measures, such as eye gaze measures, in a logical manner and comprehensively infer the driver's cognitive state. Because the mechanisms of cognitive distraction have not been precisely described a top-down, theory-driven approach is not feasible. Although some theories, like ACT-R, have been used to make predictions regarding driver distraction, they are often better at describing, rather than predicting, performance and cannot be used as a sole method for detecting cognitive distraction. Therefore the detection requires a bottom-up data mining approach.

Data mining methods have been used to detect cognitive distraction. Zhang et al. (2004) used a decision tree to estimate drivers' cognitive workload from eye glances and driving performance. In previous studies, Support Vector Machines (SVMs) and Bayesian Networks (BNs), successfully detected cognitive distraction from eye movements and driving performance (Liang, Lee et al., 2007; Liang, Reyes et al., 2007). The following sections describe these previous studies.

Support Vector Machines to detect cognitive distraction

This work was published in IEEE Transactions on Intelligent Transportation Systems (Liang, Reyes et al., 2007). In the study, Support Vector Machines (SVMs) was applied to detect driver cognitive distraction from drivers' eye movements and driving performance. Originally proposed by Vapnik (1995), SVMs are based on statistical learning theory and can be used for pattern classification and to infer non-linear relationships between variables (Cristianini & Taylor, 2000; Vapnik, 1995). Figure 8 shows the basic concept of classification using SVMs in a two dimensional space. Labeled binary-class training data, $D = \{(x_i, y_i)\}_{i=1}^{l}$ where x_i is a vector containing multiple features, and y_i is a class indicator with a value of either -1 or 1. These classes are shown as circles and dots in the Figure 8, respectively. They are mapped onto a high-dimensional feature space through a function Φ. The function Φ is written in the form of a kernel function, $K(x_i, x_j) = \Phi(x_i)^T \Phi(x_j)$ and used in the SVM calculation. When the mapped data are linearly separable in the feature space, a hyperplane that maximizes the margin from it to the closest data points of each class exists. The hyperplane yields a nonlinear boundary in the input space. The maximum margin presents the minimized upper bound of generalization error. When data are not linearly separable in the feature space, the positive penalty parameter, C, allows for training error ε by specifying the cost of misclassifying training instances (Hsu, Chang, & Lin, 2008).

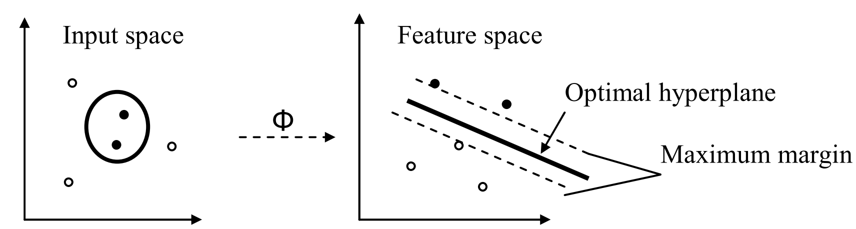


Figure 8. An illustration of support vector machine algorithm.

SVMs present several advantages over other approaches that make assumptions of linearity and normality in detecting cognitive distraction (Liang, Reyes et al., 2007). First, although some linear algorithms can account for many elements of human behavior the relationship describing human behavior is seldom strictly linear. SVMs can generate both linear and nonlinear models with equal efficiency by using different kernel functions (Amari & Wu, 1999; Vapnik, 1995). Second, SVMs can extract information from noisy data and avoid overfitting by minimizing the upper bound of the generalization error (Byun & Lee, 2002; Vapnik, 1995). SVMs produce more robust models compared to the linear-regression algorithms that minimize the mean square error, which can be seriously affected by outliers.

Data used in the study were collected using a simulator. Nineteen summarized performance measures were used to detect cognitive distraction. The study compared SVMs and logistic regression and examined three factors that might influence distraction detection: distraction definition, input combination, and time constant of performance indicators. The results showed that SVM models were able to detect driver distraction with an average accuracy of 81.1%, outperforming traditional logistic regression models. The best-performing model (96.1% accuracy) resulted when distraction was defined using DRIVE distraction definition (i.e., IVIS drive or baseline drive), the input data were comprised of eye movement and driving measures, and these data were summarized over a 40-second window with 95% overlap of windows. Figure 9 shows an example of the prediction of the SVM models. These results demonstrate that eye movements and simple measures of driving performance can be used to detect driver distraction in real time. Nonetheless, SVMs do not consider time-dependent relationship between variables, and the resultant SVM model is like a black box and cannot present the relationships learned from data in an interpretable way. To address these limitations of SVMs, a new technique—Bayesian Networks—was considered to improve the detection of cognitive distraction.

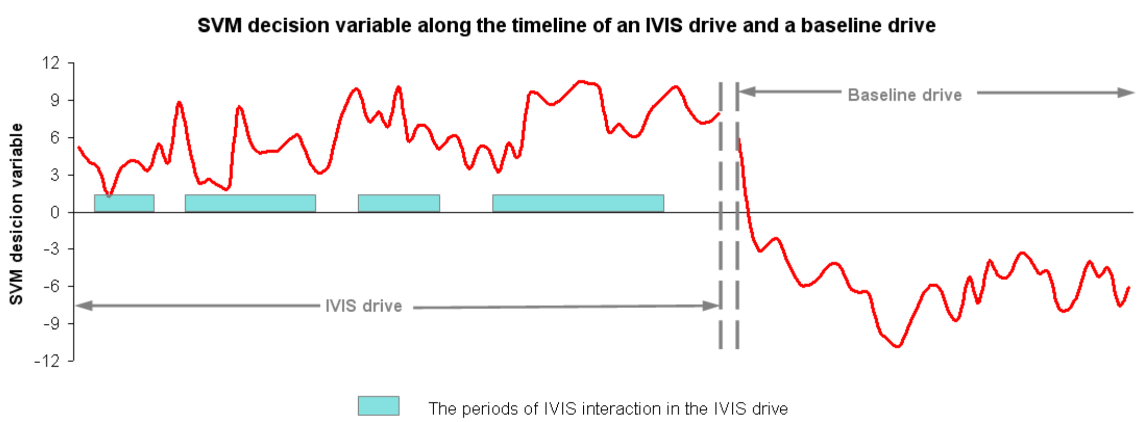
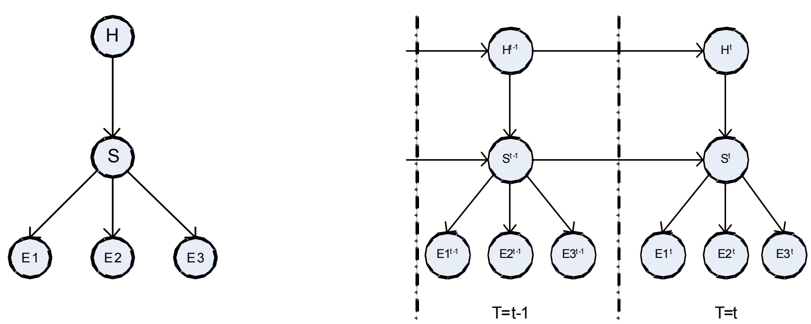


Figure 9. The SVM decision variable along the timeline of an IVIS drive and a baseline drive for participant SF7. (Liang, Reyes et al., 2007)

<u>Bayesian Networks to detect cognitive distraction</u>

This study was published in Transportation Research Record: Journal of the Transportation Research Board (TRR) (Liang, Lee et al., 2007). The study applied Bayesian Networks (BNs), another data mining method, to develop a real-time approach to detecting cognitive distraction using drivers' eye movements and driving performance. Bayesian Networks (BNs) represents a probability-based approach that presents conditional dependencies between variables. A BN includes nodes depicting random variables and arrows depicting conditional relationships. For example, in Figure 10a the arrow between variable nodes *H* and *S* indicates that *S* is independent of all variables other than *H*. BNs are either Static (SBNs) or Dynamic (DBNs). SBNs (Figure 10a) describe the situations that are not affected by previous states. DBNs (Figure 10b) connect two identical SBNs at successive time steps and model a time-series of events according to a Markov process. The state of a variable at time *t* depends on either variables at time *t* or time (*t*-1) or both. For example, the state of S^t depends on both S^{t-1} and H^t.



(a) Static BN (b) Dynamic BN

Figure 10. Examples of a SBN and a DBN.

Like SVMs, BNs can model complex, non-linear relationships. However, BNs aim to identify relationships between variables and use these relationships to generate predictions. BNs can explicitly present the relationships learned from data in an intuitive network format that can be organized in a hierarchical matter. As a result, studying trained BN helps identify cause-effect links between variables. Moreover, DBNs can model time-dependency between variables. BNs are broadly applicable to human-behavior modeling and have been used to detect affective state (Li & Ji, 2005), fatigue (Ji, Zhu, & Lan, 2004), lane change intent during driving (Kumagai & Akamatsu, 2006), pilot workload (Guhe et al., 2005), and driver cognitive distraction (Liang, Lee et al., 2007).

BN models were trained and tested to investigate the influence of three model characteristics on distraction detection: time-history of driver behavior, the inclusion of hidden nodes in the model structure, the way in which data is summarized, and length of training sequences. The results showed that BNs could identify driver distraction reliably with an average accuracy of 80.1%. Dynamic BNs (DBNs) that consider time-dependencies of driver behavior produced more sensitive models than Static BNs (SBNs). Longer training sequences improved DBN model performance. Blink frequency and fixation measures were particularly indicative of distraction. These results demonstrate that BNs, especially DBNs, are able to detect driver cognitive distraction by extracting information from complex behavioral data. The results from both studies suggest that SVMs and BNs are promising techniques in detecting cognitive distraction. However, SVMs and BNs were not directly compared. A third study was conducted to make direct comparisons between SVMs and BNs.

<u>A comparison of SVMs and BNs in detecting cognitive distraction</u>

This work was published as a book chapter in Passive Eye Monitoring: Algorithms, Applications and Experiments (Liang & Lee, 2008). The purpose of the chapter was to compare SVMs, SBNs, and DBNs in detecting driver cognitive distraction using the best parameter settings from the same dataset used in the previous two studies. DBNs, which model time-dependent relationships between driver behavior and cognitive state, produced the most accurate and sensitive models compared to SBN and SVM (Figure 11). This indicates that changes in drivers' eye movements and driving performance over time are important predictors of cognitive distraction. At the same time, the SVM models detected driver cognitive distraction more accurately than the SBN models (Figure 11). This suggests that the SVM learning technique has some advantages over the BN technique. SVMs have fewer computational difficulties than BNs. It took less than one minute to train a SVM model, but approximately half an hour for SBNs and even longer for DBNs using the same training data.

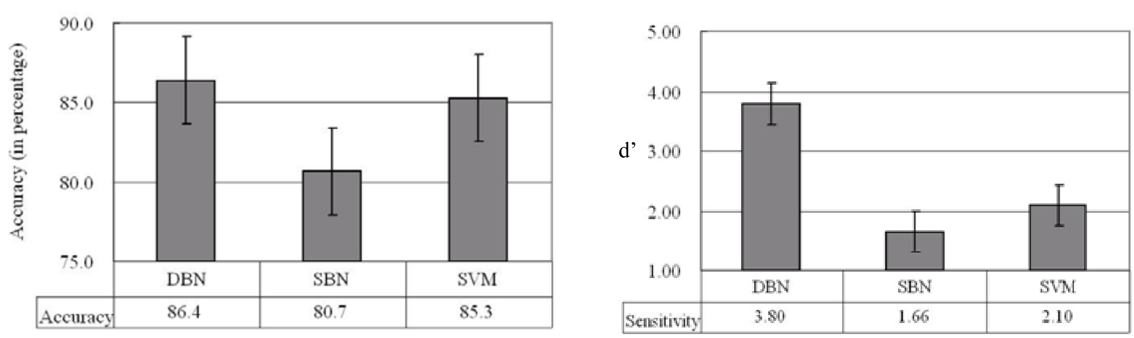


Figure 11. Comparisons of testing accuracy and d'. (Liang & Lee, 2008)

Improved detection of cognitive distraction: Hierarchical structure to combine multiple algorithms

Based on the comparisons of SVMs and BNs, it may be possible to develop a new approach to detect cognitive distraction, which is expected to be accurate and computationally efficient. A promising approach to accomplishing this goal is to combine DBNs, which consider time-dependent relationships between driver behavior and cognitive state, and feature reduction methods (e.g., clustering).

Many data fusion architectures can combine different algorithms. Esteban and his colleagues (2005) summarized various data fusion architectures and proposed a robust strategy to implement fusion systems. With so many diverse applications, it is impossible to establish a one-fits-all framework. Esteban and his colleagues reviewed six architectures that had been used in data fusion applications with potential for generalization to other application. The six frameworks included Joint Directors of Laboratory (JDL), Thomopoulos architecture, multi-sensor integration fusion model, behavioral knowledge-based data fusion model, waterfall model, and distributed blackboard data fusion architecture. The most common architectures were in hierarchical form (e.g., the JDL and waterfall model) and have been used to build complex, large-scale systems, such as military surveillance systems. In the hierarchical structure, different algorithms or models can be used to implement various functions at the different layers, and the best performing techniques can be chosen for each function to boost the efficiency of the systems.

Compared to complex military applications, the detection model for driver distraction is relatively simple, but might also benefit from using a hierarchical structure to integrate the measures from multiple sources. This structure has been demonstrated to be effective in some other relatively simple detection systems, similar to that of cognitive distraction. Oliver and his colleagues (2004) combined two Hidden Markov Models (HMMs) in a cascade fashion to identify office activities from multiple sensory channels.

Another study combined a Dynamic Bayesian Clustering and SVM model in sequence to forecast electricity demand (Fan, Mao, Zhang, & Chen, 2006). All these models have two layers. The lower-layer model summarizes basic measures into more abstract characteristics of the target, and the higher-layer model classifies examples based on these characteristics. This approach can reduce the computational load and makes it easy to track the contributions of model inputs with respect to the ultimate classification. DBNs and feature reduction methods can be combined in many different ways. One promising way is to use feature reduction method to build models that can identify behavioral patterns from performance measures and then use DBN models to infer cognitive states based on the identified patterns.

Limits of previous research and objectives

Both visual distraction and cognitive distraction undermine safety. One approach to increase safety is to develop a distraction mitigation system that can detect distraction and support mitigation strategies that guide driver behavior and maintain safety. Real-time detection of driver distraction is a crucial function of such a system. Because the effects of driver distraction can be complicated and human behavior is continuous in time, current detection techniques may not be robust enough to identify the distraction. More systematic and sophisticated approaches are needed.

Although many algorithms have been used to assess the association between visual distraction and increased crash risk (Donmez et al., 2007; Engström & Mårdh, 2007; Senders et al., 1967; Wierwille & Tijerina, 1998; Zhang et al., 2006), no comparisons between different algorithms have been made. Although two data mining techniques, Support Vector Machines and Dynamic Bayesian Networks, have been successfully used to detect cognitive distraction (Liang & Lee, 2008; Liang, Lee et al., 2007; Liang, Reyes et al., 2007), these algorithms are imperfect. SVMs can describe complicated relationships, but ignore time dependence of driver behavior; and DBNs can model time-dependent relationships, but are not computationally efficient in capturing relationships between a large number of inputs and the presence of distraction (Liang & Lee, 2008). Moreover, visual distraction and cognitive distraction often occur in combination. When the two types of distraction occur simultaneously, their effects on driver behavior might interact. In such cases, the detection algorithm for a single type of distraction may be inadequate. Accurate estimation of driver distraction requires robust algorithms to detect a single type of distraction, and a mechanism to integrate the detection of both types of distraction. To date, this integration mechanism has not been developed.

To fill the gaps in the detection of distraction, research in this dissertation seeks to improve algorithms for real-time detection of both visual distraction and cognitive distraction individually and to develop a strategy that can identify the co-occurrence of both types of distraction. The major contributions of this dissertation include 1) applying data mining and other quantitative methods to implement accurate real-time detection for two major types of distraction: visual and cognitive, and 2) investigating how visual distraction and cognitive distraction interact and influence driver performance and estimating the combined distraction-related impairment. The outputs of this dissertation are expected to benefit the development of adaptive in-vehicle systems. To make these contributions I achieved the following specific aims.

- Aim 1: Developing a layered algorithm to improve the detection of cognitive distraction
- Aim 2: Developing and comparing algorithms to estimate visual distraction using naturalistic data
- Aim 3: Investigating the interaction of visual and cognitive distraction and developing a sequential strategy to detect combined distraction

CHAPTER III. USING A LAYERED ALGORITHM TO DETECT COGNITIVE DISTRACTION

The detection of driver cognitive distraction is a great challenge in developing a distraction mitigation system because the effects of cognitive distraction are subtle and inconsistent and no overt behavioral indicator can predict this distraction. My previous studies show that the detection of cognitive distraction should integrate many performance indicators, such as driving performance and eye gaze measures, and consider their changes in a relative long period of time, such as 30 seconds (Liang & Lee, 2008; Liang, Lee et al., 2007; Liang, Reyes et al., 2007). Such comprehensive and temporal view of driver behavior can be obtained by using data mining algorithms. Shown by my previous studies, two data mining methods, SVMs and DBNs, are promising techniques to detect cognitive distraction with accuracy above 85%. However, these algorithms either captured only limited effects of cognitive distraction on driver behavior or lacked computational efficiency. Although the SVM algorithms can efficiently describe complex relationships between driver behavior and cognitive state, the algorithms cannot describe the time dependence and the resultant SVM models cannot describe the relationship between driver behavior and cognitive states. DBN algorithms can model time-dependent relationships, but are much less efficient when a large numbers of performance measures were used as inputs, such as 19 measures in my previous studies.

To address these limitations of the current techniques and obtain accurate and fast detection algorithms for cognitive distraction, I designed a hierarchical/layered algorithm. This layered algorithm includes a DBN algorithm at the higher level to model the time-dependent relationship of driver behavior and a novel clustering algorithm —supervised clustering—at the lower level to identify feature behaviors when drivers are in different cognitive states and reduce the input space of the DBN algorithm. The results demonstrate that the layered algorithm overcomes the disadvantages of DBNs and significantly improves computational efficiency in training and prediction. This new algorithm can also help to identify the meaningful relationships between driver behavior and cognitive state, which SVMs and traditional statistical analysis methods cannot.

The layered algorithm

The proposed algorithm depicted in Figure 12 has two layers: three cluster models at the lower layer and a DBN algorithm at the higher layer. In this structure, the DBN algorithm recognizes driver cognitive state based on the outputs of the cluster models with consideration of time dependence. The cluster models identify feature behaviors represented by cluster labels from three groups of performance measures, one model from each group. With the cluster models at the lower layer, this layered algorithm can improve the single-layered DBN algorithm, which imposes a large computational load, by reducing the input space of DBNs from 19 inputs in my previous study to 3 inputs. In this way, the computational load for training a DBN and using the DBN to predict driver cognitive state can be substantially reduced. The layered algorithm can describe time-dependent relationships in human behavior with computational efficiency and is also expected to provide meaningful insights about the effects of cognitive distraction on driver behavior.

Lower-layer clustering

In the lower layer, three cluster models recognized feature behaviors from the three groups of performance measures. The cluster models were constructed using supervised clustering, which identified clusters for a classified dataset so that each cluster comprised of the data approximately belonging to one class. Three groups of performance measures included eye movement temporal measures, eye movement spatial measures, and driving performance measures, each of which presented one aspect of driver behavior (Table 3). These three groups were categorized from the original 19 performance measures in my previous studies based on their correlations and meanings. The performance measures were summarized in the same way as my pervious study (Liang & Lee, 2008) — across 30-second time windows and no overlap between windows. Cluster labels identified by a model represented the feature behaviors of the cognitive state that the majority cases in the clusters belonged to, and these labels were used as the inputs of the DBN algorithm at the higher layer.

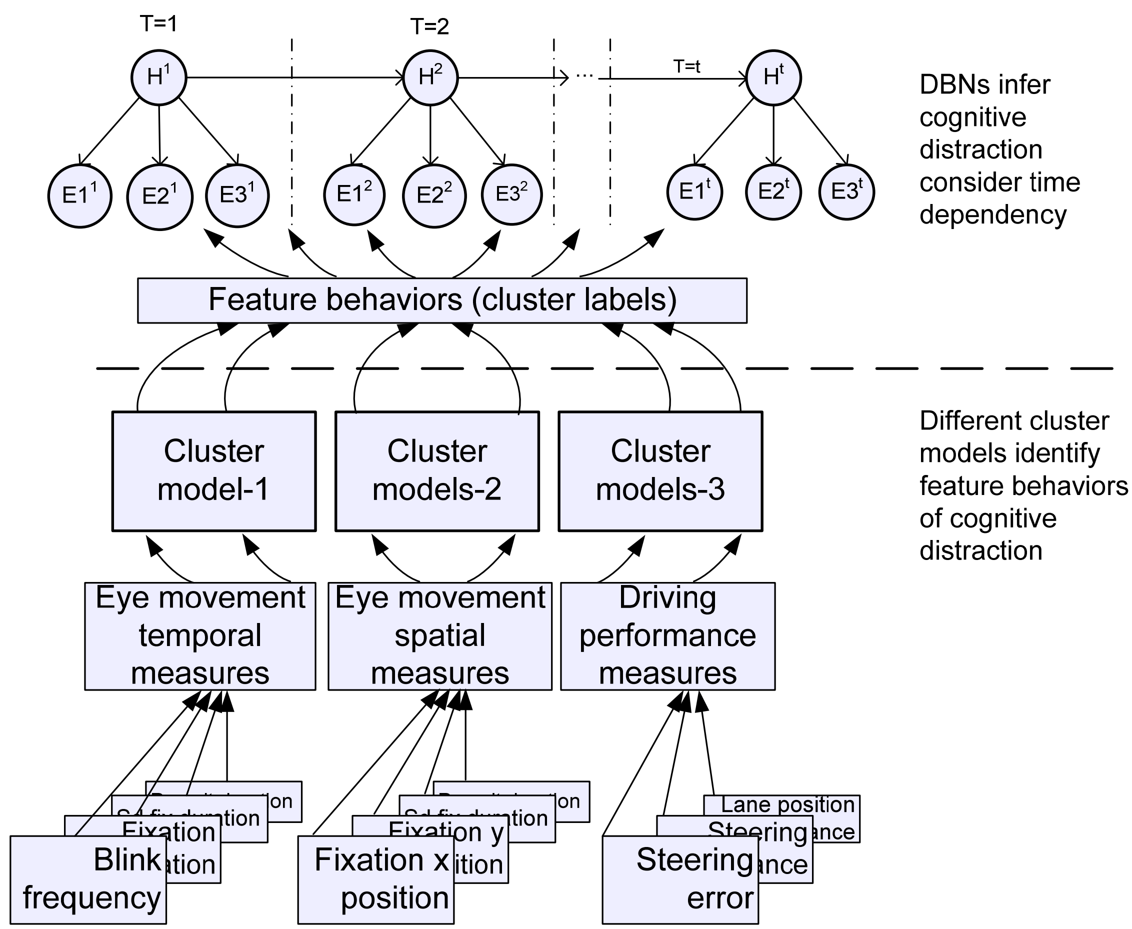


Figure 12. The structure of the layered algorithm. The curving, solid arrows indicate data flow. The straight, lined arrows in the DBN algorithm indicate cause-effect relationships between variables.

Table 3. Three groups of performance measures

Groups	Performance measures
Eye movement temporal measures	blink frequency, mean and standard deviation (SD) of fixation duration, pursuit duration, pursuit distance, pursuit speed, and percentage of the time spent on performing pursuit movements
Eye movement spatial measures	mean and SD of horizontal and vertical fixation location coordinates and direction
Driving performance measures	SD of steering wheel position, mean steering error, and SD of lane position

Higher-layer DBNs

A DBN algorithm inferred driver cognitive state from feature behaviors. H^t and $Ei^t, i=1,2,3$ in Figure 12 represented driver cognitive state and feature behaviors with a time stamp, and the arrows represent the cause-effect relationships between cognitive state and behaviors. The general structure of this DBN allowed for the across-time arrow occurring only between the cognitive states at two consecutive time steps. This assumption followed the intuition that driver cognition state determines their behavior. The training procedure of the DBN algorithm included structure learning, which tested the existence of conditional dependencies between variables, and parameter estimation, which determined the parameters of the relationships (i.e., the strength of the conditional dependency).

Supervised clustering

Traditional clustering is an unsupervised data analysis technique that partitions data into the subsets whose elements share common traits. Different from traditional clustering, supervised clustering is a supervised analysis and categorizes classified data. This technique ensures that the majority of data in each resultant cluster comes from one class. For a cognitive state, more than one cluster may be identified. Therefore, supervised clustering may discover some heterogeneous effects of cognitive distraction.

For example, cognitive distraction may lead to either longer or shorter fixation duration under different circumstances than attentive driving (Zhang et al., 2004).

Supervised clustering minimizes cluster impurity and the number of clusters, which is also different from the traditional clustering. Equation 1 represents an example of the optimization problem of supervised clustering.

$$\text{Minimize} \quad q(X)=\text{Impurity}(X)+\beta\cdot\text{Penalty}(k)$$

$$\text{Impurity}(X)=\frac{\text{\# of data in minor classes}}{n} \qquad (1)$$

$$\text{Penalty}(k)=\begin{cases}\sqrt{(k-c)/n} & k\geq c\\ 0 & k\leq c\end{cases}.$$

where X is a clustering solution, β is the weight to balance the impurity and penalty of large number of clusters, k is the number of clusters in X, n is the total number of training data, and c is the number of classes in the data (Zeidat, Eick, & Zhao, 2006). The cluster impurity reflects the percentage of the data in minor classes, which take smaller proportion of data in a cluster than another class (Eick, Zeidat, & Zhao, 2004). The number of clusters can be adjusted using the penalty term for large number of clusters ($\beta\cdot\text{Penalty}(k)$).

The two terms of the optimization problem for supervised clustering (Equation 1) demonstrate its advantages over traditional clustering when dealing with classified data, making it suitable for identifying feature behaviors of drivers under two different cognitive states. First, minimizing the impurity of clusters ensures that each cluster can represent one class, or in this case one cognitive state. As an illustration, cluster 1 (Figure 13A) created by traditional clustering contains the data from two classes denoted by circles and dots, while supervised clustering tends to split this cluster into two clusters, i.e., cluster 1' and 1" (Figure 13B). In this way, the data describing two different cognitive states of drivers will not be miss-categorized in one cluster. Second, minimizing the number of clusters can simplify the results. In this study, supervised clustering reduced the input space for the DBN algorithm at the higher layer, and therefore the large number of clusters should be avoided. For example, two close clusters, cluster 3 and 4, that were produced by traditional clustering (Figure 13A) are merged into one big cluster 3' by supervised clustering (Figure 13B). Thus, supervised clustering can integrate existing knowledge of the data (i.e., original classification of data) to clustering results to enhance the performance of other classification algorithms (Eick et al., 2004). This method has been successfully applied to detect intrusive activities in computer networks (Li & Ye, 2005) and identify possible gene subsets that determine human tissue formation (Dettling & Bühlmann, 2002).

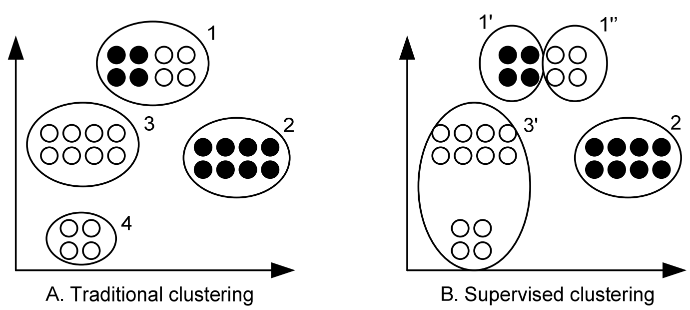


Figure 13. Difference between traditional and supervised clustering. The circles and dots represent the classes defined before clustering. (Eick et al., 2004)

The training of supervised clustering can be implemented by searching for the optimal solution defined by the value of the fitness function (q in Equation 1). The solution comprises of a set of representatives selected from the training dataset. Each representative serves as the centroid of one cluster, and cluster membership is determined by Euclidean distance from other data points to these representatives. The searching followed the optimization procedure described in Table 4, called Single Representative Insertion/Deletion Steepest Decent Hill Climbing with Randomized Restart (SRIDHCR) by

Zeidat et al. (2006). Supervised clustering is expected to identify the clusters that can reflect driver characteristic behaviors associated with different cognitive states.

Table 4. The pseudo-code of SRIDHCR

Single Representative Insertion/Deletion steepest decent Hill Climbing with Randomized restart (SRIDHCR) REPEAT *r* TIMES Set an initial solution: *curr* = a set of representatives selected randomly from the training set (two or three representatives for the dataset with two classes) Determine cluster membership and calculate *q*(*curr*) WHILE not done DO 1. Create a new set of solutions *S* by adding a non-representative or removing a representative from *curr* ($S=(s_1,s_2,\ldots s_m)$) 2. Find minimal *q* at the solution s_i in *S* 3. IF $q(s_i)$ <$q(curr)$, THEN *curr*= s_i ELSE IF $q(s_i)$ =$q(curr)$ AND Impurity(s_i)<Impurity$(curr)$, THEN *curr*= s_i ELSE terminate and return *curr* as the solution for this run END END Find the final solution from the results of the *r* runs that has minimal *q*

Training and evaluation of the layered algorithm

To briefly summarize this section, the layered algorithm was compared with two alternatives. One was the single-layered DBN algorithm developed in my previous study (Liang & Lee, 2008); another was the SVM algorithm considering the performance measures at two consecutive time steps—last and current. This evaluation procedure used the same experimental data as my previous studies (Liang & Lee, 2008; Liang, Lee et al., 2007; Liang, Reyes et al., 2007). In the experiment, in-vehicle sensor systems recorded driver eye movements and performance. The experimental conditions defined driver cognitive states: cognitive distraction and no distraction. All algorithms were constructed for each driver and trained and tested with the same training and testing data sets. Testing accuracy, signal-detection-theory measures (hit and false alarm rate, *d'*, and response bias), CPU time to train and test the algorithms, and the percentage of inefficiently-predicted cases in the testing sets were used to evaluate the algorithms.

Experimental data

The experiment took place in a fixed-based, medium-fidelity driving simulator and included six 15-minute drives: four IVIS drives and two baseline drives. During each IVIS drive, participants completed four separate interactions with an auditory stock ticker, which had one-minute break in between. During each interaction, participants continuously tracked the price changes of two different stocks and reported the overall trend of the changes at the end of the interaction. In the baseline drives, participants did not perform the IVIS task. During all drives, participants were instructed to maintain vehicle position as close to the center of the lane as possible, to respond to the intermittent braking of a lead vehicle, and to report the appearance of bicyclists in the drive scene. Eye movement and driving performance data were collected at a rate of 60 Hz for nine participants using a Seeing Machines faceLAB™ eye tracker and the driving simulator, respectively. Further details of the experiment and data reduction can be found in (Liang, Reyes et al., 2007).

The distraction definition specifies the conditions when the drivers were cognitively distracted. In this study the distraction was defined by IVIS drives, and no-distraction by baseline drives, called DRIVE definition. This definition clearly separates two cognitive states by disconnected time periods. My previous study has shown that the SVM algorithms using the DRIVE definition performed best (Liang, Reyes et al., 2007).

After the reduction, each row in the data set, called instance hereafter, includes 19 continuous measures of eye movements and driving performance summarized over 30-second time window and corresponding driver cognitive state in that window. These 19 performance measures were divided into three groups based on their correlation and meanings —eye movement temporal measures, eye movement spatial measures, and driving performance measures, each of which presented one aspect of driver behavior (Table 3).

Training procedure of the layered algorithm

The layered algorithm was trained for each driver because cognitive distraction affects driver behavior in a subtle, inconsistent manner, which can be easily washed out by individual differences associated with driving style. The distraction was defined using experimental conditions. Consequently, the data for different drivers were preprocessed individually in two steps. First, because supervised clustering uses distance to evaluate the separation of data, the magnitude of the variables needs to be scaled to the same range to eliminate the domination of some measures simply because of their scale. The data were normalized for each driver by calculating z-scores. Then, the normalized data were randomly divided into training and testing datasets. A training data set contained multiple sequences of the instances and took two thirds of the total data from one driver, and the rest of one third served as the testing data. The algorithms were trained with only the training data, and the testing data were considered as "unseen" cases to evaluate the algorithms.

The training procedure included constructing the cluster models at the lower layer and training the DBN algorithm at the higher layer. To train the cluster models, I implemented the SRIDHCR algorithm using the program language of Matlab R2006b. The parameter settings of the optimization were either arbitrarily selected or adjusted to limit the number of clusters. The number of iterations (*r* in Table 4) was 100, the initial number of clusters was four, the cluster impurity was calculated according to Equation 1, and the penalty term for the number of clusters was $k/200$ (k: the number of clusters). The final number of clusters for the cluster models ranged between three and six.

The DBN training consisted of structure learning, which tested the existence of conditional dependencies between variables, and parameter estimation, which calculated the strength of these dependencies. The training data of the DBN algorithm included three cluster labels, each from one cluster model, and drivers' cognitive state defined by DRIVE definition. The general structure of this DBN allowed for the across-time arrow occurring only between the cognitive states at two consecutive time steps, as shown in Figure 12. This assumption followed the intuition that driver cognition state determines their behavior. The DBN algorithms were trained using the same Matlab toolbox (Murphy, 2004) and accompanying structure learning package (LeRay, 2005) as my previous studies (Liang & Lee, 2008; Liang, Lee et al., 2007).

Alternative algorithms

The layered algorithm was compared with two other alternative algorithms. One algorithm was the single-layered DBN with 19 performance measures, the best detection algorithm for cognitive distraction developed in my previous study (Liang & Lee, 2008). But, this algorithm had large computational load due to a large number of performance measures. The other alternative algorithm was the SVMs with the 19 performance measures at the last and current time steps as inputs. My previous study argued the disadvantage of SVMs in detecting driver cognitive distraction stems from its inability to consider time-dependent relationship in human behavior, but SVMs can more easily deal with the large number of inputs than DBNs (Liang & Lee, 2008). Adding performance measures at the previous time points to the SVM algorithms presented an approach for SVMs to considering historic change in human behavior.

The inputs of this SVM models are 38 (19x2) continuous performance measures, including 16 eye movement and 3 driving performance measures at two consecutive time points. The Radial Basis Function (RBF), $K(x_i, x_j) = e^{-\gamma|x_i - x_j|^2}$, was chosen as the kernel function, where x_i and x_j represent two data points and γ is a pre-defined positive parameter. With this very robust kernel function, it is possible to implement both non-linear and linear relationship by manipulating the values of γ and the penalty parameter

C, a pre-defined positive parameter used in the training calculation (Hsu et al., 2008). To choose the appropriate parameters, we searched for *C* and γ in the exponentially growing sequences ranging from 2^{-5} to 2^{5} using 10-fold-cross-validation (Chang & Lin, 2001). "LIBSVM" Matlab toolbox (Chang & Lin, 2001) was used to train and test the SVM models.

Model evaluation and interpretation measures

The prediction performance of the algorithms was evaluated using five different measures. The first one was testing accuracy, the ratio of the number of data correctly identified by the models to the total number of testing data. The other four measures were associated with signal detection theory: hit and false alarm rate, *d'*, and response bias, which were calculated according to Equation 2 and 3.

$$ln(response\ bias) = \frac{|\Phi^{-1}(FA)|^2 - |\Phi^{-1}(HIT)|^2}{2} \qquad (2)$$

$$d' = \Phi^{-1}(HIT) - \Phi^{-1}(FA) \qquad (3)$$

where *HIT* is the rate of correct recognition of distracted cases, *FA* is the rate of incorrect identification of distraction among not-distracted cases, and Φ^{-1} converts the probability into *z*-score. Higher hit rate and lower false alarm rate are better because a good detection algorithm should have not only high hit rate so that the distraction mitigation system can help drivers to avoid risky behavior, but also reduces false alarm as much as possible so that it does not annoy drivers with irrelevant alerts. *d'* represents the ability of the model to detect driver distraction. The larger the *d'* value, the more effectively the model detects distraction. *Response bias* signifies the bias of the model. When the bias equals zero, the model classifies cases neutrally, and false alarms and misses (not detecting distraction when it is present) tend to occur at similar rates. When the bias is less than zero, cases are classified more liberally and there is a tendency to overestimate driver distraction and to have higher false alarm rates than miss rates (1-*HIT*). When the bias is greater than zero, cases are classified more conservatively, and there is a tendency to underestimate driver distraction and have more misses than false alarms. Both *d'* and response bias can affect testing accuracy. Separating *d'* and response bias makes for a more refined evaluation of the detection models than a simple measure of accuracy (Stanislaw & Todorov, 1999).

Besides the prediction performance, the training efficiency of the algorithms was also important. The layered algorithm used supervised clustering to reduce the input space of the DBN algorithm, which was expected to reduce the overall training and prediction efforts from the single-layered DBN algorithm. To measure this efficiency, I used the time to train and test algorithms and the rate of incompletely-predicted testing data. The time to train and test algorithms was defined as computer CPU time spent training or testing different algorithms. The computer used in this study was a SONY VAIO laptop with Intel® Core™2 CPU (T5500 @ 1.66GHz) and 1GB of RAM. The Matlab software ran on Microsoft Windows XP Service Pack 3, and no other applications running at the same time. The training of the DBN models might be incomplete because of the limits of the training data. The parameter estimation procedure of DBNs involves identifying conditional probabilities of each feature behavior (or performance indicator value) for a given driver cognitive state. Some combinations of feature behaviors and cognitive state were not included in the training set, but occurred only in the testing set. Although the training algorithm could assign an arbitrarily small probability for these missing combinations in the training set so that the resultant DBN could estimate an approximate value for testing data with these combinations, it still presented the case of incomplete training. This incompleteness was measured by the percentage of testing data that involved these missing combinations.

The above measures evaluate the overall performance of the detection algorithms. The strength of dependencies between performance measures and driver cognitive state was assessed by the normalized variant of the mutual information (C_{XY}), also called coefficients of constraint or uncertainty coefficient (Equation 4).

$$C_{XY} = \frac{I(X;Y)}{H(X)} = 1 - \frac{H(Y|X)}{H(Y)} \quad (4)$$

where *X*, and *Y* are two random variables, *I(X;Y)* represents mutual information of *Y* given *X*, *H(Y)* is the entropy of *Y*, and *H(Y|X)* is the entropy of *Y* given *X*. Mutual information, *I(X;Y)*, describes the information shared by two random variables, *X* and *Y* (Guhe et al., 2005), that is, how much uncertainty of *Y* is reduced by knowing *X*. Its normalized variant describes the percentage of the uncertainty of *Y* is reduced by knowing *X*. Although the normalized variance can be calculated from raw data, calculation from the resultant DBN algorithm helps to examine whether the algorithm captures the relationships between variables in the dataset. Based on the trained layered algorithm, the normalized variant of the mutual information of each behavioral characteristic (feature behaviors) and cognitive distraction was calculated according to Equation 4. *X* represents a feature behavior, and *Y* represents driver cognitive distraction. The higher C_{XY}, the more indicative the feature was to driver cognitive distraction.

Results and discussion

Algorithm comparison

A one-way (model types: the layered algorithm, DBN, and SVM) comparison of five model-performance measures was conducted using Friedman's non-parametric test. The rationale of using the non-parametric test was that there were only nine data points for each algorithm, one from each driver, and the data might not satisfy the assumptions of an ANOVA.

The layered, single-layered DBN and SVM algorithms produced similar prediction performance, and all five measures were not statistically different between different algorithms (Table 5). However, the layered algorithm and SVMs showed some advantages over the single-layered DBNs in training and testing efficiency. First, the training and testing time reduced greatly from the single-layered DBN algorithm to the layered and SVM algorithms (Table 5). To train the layered or SVM algorithm for each driver required 13-17 seconds on average, in contract to 1146 seconds (19.1 minutes) required for the single-layered DBNs. Second, the layered and SVM algorithms could reliably detect distraction for almost all testing data while the single-layered DBNs could detect for only 60 percent of testing data (Table 5). The inefficiency to detect some data was caused by the limited training data. The single-layered DBNs had 19 inputs and each input had 5-14 values, but the DBNs in the layered algorithms had only three inputs and each input had 3-6 values, which should significantly reduce the needs of data to train a reliable model. The results on inefficient-predicted cases reflected the advantage of the layered algorithm over the single-layered DBN algorithm. These two analyses suggest that the layered algorithm improves computational efficiency from the single-layered DBNs and is more practical to be used in the real-world distraction detection.

Table 5. The results of algorithm comparisons.

	Layered algorithm mean (SD)	**SVMs mean (SD)**	**DBNs mean (SD)**	**Friedman's test χ^2_2 (p-value)**
Accuracy (%)	88 (8)	90 (5)	88 (16)	0.67 (0.72)
d'	3.50 (1.81)	3.06 (1.37)	4.80 (2.54)	1.56 (0.46)
Response bias	1.82 (4.38)	-1.36 (3.64)	-0.22 (4.47)	1.56 (0.46)
Hit rate	0.88 (0.08)	0.94 (0.04)	0.92 (0.14)	2.29 (0.32)
False alarm rate	0.14 (0.16)	0.23 (0.14)	0.16 (0.23)	1.31 (0.52)
Training CPU time (s)	13 (2)	17 (4)	1146 (131)	14.89 (0.0006)
Testing CPU time (s)	0.95 (0.12)	0.17 (0.03)	5.91 (0.73)	18.00 (0.0001)
incompletely-predicted (%)	1.13 (0.03)	0 (0)	40 (21)	17.43 (0.0002)

Note: The standard deviation is presented in parentheses.

For the layered algorithm, the analysis on the normalized variants of mutual information for three behavioral characteristics was consistent with my previous study (Liang, Lee et al., 2007). My previous results on the single-layered DBN algorithm shows that blink frequency is the most indicative measure and spatial distribution of eye movements and fixation duration also signifies driver cognitive state (Liang, Lee et al., 2007). This study found that eye movement temporal measures including blink frequency and fixation duration obtained the highest normalized variant (56%), followed by eye movement spatial measures (45%) and driving performance measures (only 23%). This suggests that the layered algorithms captured similar information from data as the single-layered DBN algorithms, which may explain the similar prediction performance for the layered and single-layered DBN algorithms. Nonetheless, it was impossible to extract such information about the relationships between driver behavior and cognitive states from the resultant SVM models.

Algorithm interpretation

Studying the layered algorithms helps to understand some effects of cognitive distraction that may not be discovered in traditional statistical analysis because supervised clustering may identify heterogeneous behaviors of drivers that occur when drivers are cognitively distracted. This benefit can be illustrated using an example model trained with the data from the driver named SM7 (Figure 14). The example identified three clusters in the lower-layer cluster models, representing three feature behaviors for each aspect of driver performance. Each feature behavior signified a cognitive state of drivers that labeled the majority cases in that cluster. Then, using these feature behaviors as inputs, a DBN algorithm detected driver distraction based on the conditional probabilities of the behaviors given the condition of “distraction” or “no distraction". The following paragraphs focus on each aspect of the driver behavior and identify the meanings of the feature behaviors regarding cognitive state.

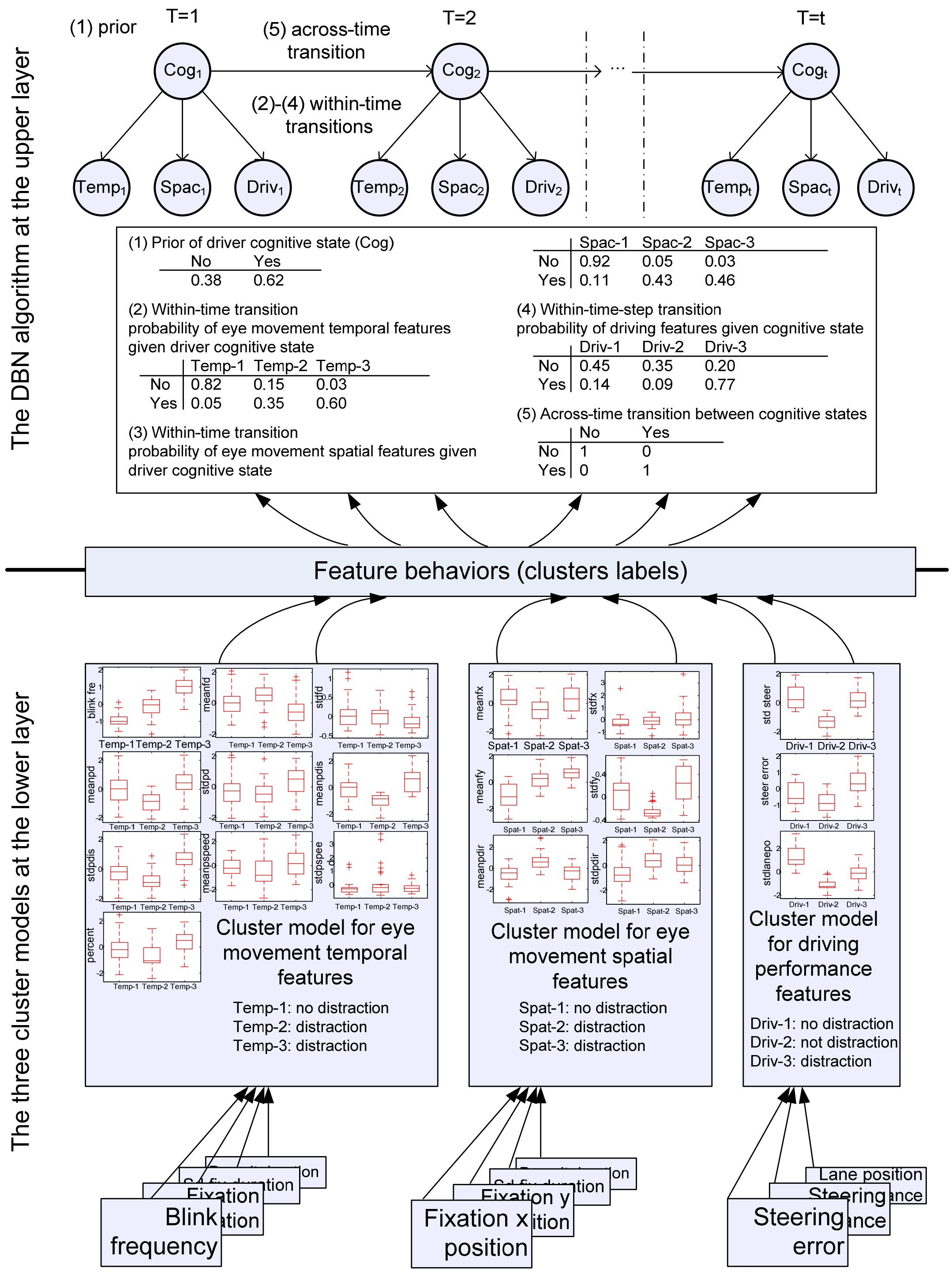


Figure 14. The example of trained layered algorithms based on the data from driver SM7.

For the eye movement temporal characteristics, the first cluster (Temp-1) contained a majority of cases under “no distraction”, and two other clusters (Temp-2 and Temp-3) contained a majority of cases under “distraction”. Comparing these clusters, the difference in the value of performance measures led to the interesting explanations for how the temporal characteristics of eye movement reflected driver cognitive state. First of all, Temp-1 had a relatively low blink frequency compared to Temp-2 and Temp-3, indicating that the driver tended to blink faster when being distracted than not. This trend was not isolated and also occurred in five of the other eight drivers. The increased blink frequency during cognitive distraction may indicate the lack of the attention to visual control, which can lead to more involuntary eye movements and may disrupt the consolidation of visual information (Strayer et al., 2003).

Another eye movement temporal measure, fixation duration, showed a bidirectional effect of cognitive distraction. Although both Temp-2 and Temp-3 indicated cognitive distraction, Temp-2 presented a relatively long duration and Temp-3 represented a relatively short duration of fixations compared to Temp-1. More interestingly, these two feature behaviors, Temp-2 and Temp-3, occurred at the different rates under cognitive distraction. Temp-3 was 1.7 times more likely to occur than Temp-2 (Temp-2: 35%, Temp-3: 60%, Figure 14). It may suggest that Temp-3 represented a typical pattern of eye movements of cognitive distraction or when the driver was fully engaged in the IVIS task. Temp-2 may depict a transitional behavior when the driver started to become, but was not fully, engaged in the task or during a short period after the task finished. This difference can be illustrated by pairing the experimental conditions and the prediction of feature behaviors (Figure 15). The training data occurring during the breaks of the IVIS tasks represented by the shaded areas were mostly labeled as Temp-2, suggesting that Temp-2 represents intermediary behavior of cognitive distraction. This bidirectional effect of cognitive distraction could not be discovered with traditional statistical analysis, like ANOVA. However, the effect of cognitive distraction on fixation duration varied substantially between drivers—some drivers had longer fixation duration and others had shorter duration when distracted.

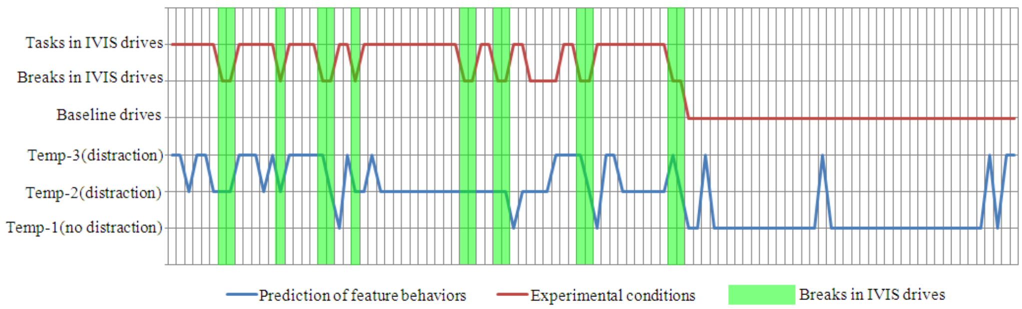


Figure 15. The prediction of feature behaviors of the eye movement temporal characteristics with the experimental conditions

For the clusters based on eye movement spatial measures, the driver looked down more when being distracted than not, indicated by the comparison of vertical position (y) of fixation location (meanfy) between the Spat-1 (feature behavior of no distraction) and the Spat-2 and Spat-3 (feature behavior of distraction) (Figure 14). The larger the vertical position, the lower the driver looked. It suggests that driver focused on the roadway closer to the subject vehicle (not at the road center) more, which may limit the driver's capacity to foresee the driving situation. Again, this effect of cognitive distraction on eye movement spatial characteristics largely depends on different individuals. Among nine drivers, there were three drivers who tended to look down, but two drivers who looked up during distraction, suggesting that driver eye-gaze patterns are somewhat idiosyncratic when visual scanning is disrupted by cognitive workload. These results are consistent with the findings of previous studies (Harbluk, Noy, Trbovich, & Eizenman, 2007; Victor et al., 2005).

The results of the cluster model for driving performance measures showed that although Driv-1 (feature behavior of no-distraction) and Driv-3 (feature behavior of distraction) shared similar steering-angle variance (std_steer, Figure 14), Driv-3 had larger steering error than Driv-1 (steer_error, Figure 14). It suggests that the driver steered more abruptly during cognitive distraction compared with no-distraction even when the range of the steering angle change was similar in the two situations. This general effect of cognitive distraction was found in a total of six out of nine drivers. At the same time, we can also see that the clusters Driv-1, Driv-2, and Driv-3 were all very likely to occur during the baseline drives (Driv-1: 0.45; Driv-2: 0.35; Driv-3: 0.20, Figure 14). But the probability of these clusters to occur in the IVIS drives differed greatly, and Driv-3 occurred dominantly over Driv-1 and Driv-2 (Driv-1: 0.14; Driv-2: 0.09; Driv-3: 0.77). It suggests that when drivers are not distracted, their driving performance varies substantially, but when they are distracted, their performance converges to a certain pattern. It may reflect driver's ability to employ many strategies to support satisfactory performance when demands are low, but relatively few strategies support satisfactory performance when demands are high (Goodrich, Stirling, & Frost, 1998).

Conclusions

Based on the results, although the layered algorithm did not improve the prediction of cognitive distraction detection, the layered algorithm significantly reduced computational load and made it possible to train the algorithms much more quickly than the single-layered DBNs, with similar prediction performance. The layered algorithm also provides useful insights concerning the effects of cognitive distraction on driving behavior, which have no equivalent in the SVM algorithm and other traditional statistical tests. Overall, the layered algorithm achieves a satisfactory detection of cognitive distraction, overcoming the shortcoming of the single-layered DBN algorithm and providing interesting insights about the effects of cognitive distraction on driver behavior. This study demonstrated that data mining methods are suitable to identify human cognitive state from performance.

However, fast and accurate identification of cognitive distraction does not present the whole story of detecting driver distraction. Compared with cognitive distraction visual distraction may impose more detrimental effects on driving, and therefore identifying visual distraction is very critical for driver distraction mitigation systems. Because visual distraction influences driver behavior differently than cognitive distraction, the methods to detect cognitive distraction are not suitable for detecting visual distraction. Moreover, the experiment data used in this chapter do not enable us to link distraction crash risk in actual driving situations. The next chapter focuses on estimating visual distraction and associating drivers' eye glance patterns with the risk of crashes using naturalistic data.

CHAPTER IV. DEVELOPING REAL-TIME ESTIMATION OF VISUAL DISTRACTION USING THE 100-CAR STUDY DATA

This chapter developed the algorithm to estimate visual distraction from drivers' eye glance patterns and associated the estimated distraction with crash risk using the naturalistic 100-Car Study data. Different from the first aim (detection of cognitive distraction), this aim was built upon the naturalistic 100-Car Study data, which enable us to connect distraction estimation with the risk of crashes in real driving. Three characteristics of eye glance patterns were used to estimate visual distraction: glance duration, history, and location. Six categories of estimation algorithms of visual distraction, which included an algorithm based on a simple metric of cumulative glance duration away from the road, "CG", used in the previous report of the 100-Car Study (Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006), were examined based on the 100-Car naturalistic data set. The results show the eye glance patterns can indicate drivers' visual distraction and crash risk. The algorithms considering the instantaneous changes of off-road glance duration produce the estimation of visual distraction that is most sensitive to crash risk. Unexpectedly, none of factors that might be expected to make such an algorithm more sensitive did. The neither the penalty for long glances (i.e., 1.5th power of glance duration), the penalty for a long sequence of glances away from the road (i.e., glance history), nor the distance a driver might look from the road (i.e., eccentricity of glance location) significantly improved the algorithms. However, an algorithm focused on instantaneous duration of glance away from the road revealed that visual distraction estimated by analyzing drivers' eye glance patterns can indicate crash risk.

Effects of visual distraction

Most secondary tasks require that drivers look away from the road. Drivers' eye glance patterns may account for much of the risk associated with secondary tasks. The results of the 100-Car Study show that complex secondary tasks, such as dialing a hand-held device and reading, increased the likelihood of crashes/near-crashes by approximately three times, producing an odds ratio (OR) of 3.10 and 95% confidence intervals (CI) of 1.72, 5.47. Moderate tasks, such as inserting/retrieving CDs and eating, increased the likelihood by two (OR 2.10, CI 1.62, 2.72) (Klauer et al., 2006). All complex tasks and most moderate tasks involved drivers' off-road glances. The study also found that looking away from road more than two seconds in a six-second period near the events increased crash/near-crash risk by at least two times relative to baseline driving (OR 2.19, CI 1.72, 2.78) (Klauer et al., 2006). Similarly, controlled experiments find that off-road glances associated with navigation systems or other in-vehicle devices undermine driving performance, leading to larger lane deviations, more abrupt steering control, and slower response to the braking of the lead vehicle braking (Dingus et al., 1989; Dingus et al., 1997; Donmez et al., 2007; Liu, 2001; Zhang et al., 2006). Although the cognitive demands of distraction activities can also undermine driving performance (Strayer & Drews, 2004; Strayer & Johnston, 2001), visual distraction may be more detrimental to safety (L. S. Angell et al., 2006).

Glances away from the road can degrade safety because critical events occur when drivers are looking away from the road or because they undermine vehicle control. In these situations drivers might fail to respond or respond only after a delay simply because they did not see the event. A series of glances away from the road might also diminish safety because the glances might undermine drivers' awareness of the driving environment. Awareness for the driving environment includes the location of other vehicles, traffic control devices, and the proximity of turns (Gugerty, 1997). This diminished awareness might cause drivers to maintain an inappropriate speed or otherwise fail to adapt to changes in the environment.

The visual demands of secondary tasks divert drivers' visual attention from safe driving, but drivers' visual attention is not determined solely by the demands of secondary tasks. Drivers actively determine when to look away from the road and coordinate when to perform secondary tasks based on the driving context. This adaptive behavior shapes eye glance patterns of drivers and may represent a critical factor in determining the risk associated with secondary task distractions. Sheridan's (2004) control-theory model of distraction provides a theoretical framework to represent this adaptive behavior of drivers. The model considers driving as a closed-loop system and secondary visual demands as a disturbance to the process of sensing the environment. Drivers switch visual attention to and away from the road to control the degree of distraction they experience. Senders et al. (1967) described such a switching process as being governed by the uncertainty of the driver regarding the roadway. This uncertainty increases according to 1.5th power of the glance away from the road so that drivers feel compelled to look back to the road as the duration of the glance away increases and a threshold of uncertainty is exceeded. Wierwille (1993) used 1.8 seconds as the threshold off-road glance duration for straight road and 1.2 seconds for curved roads. A more complex model –SEEV – that considers Salience, Effort, Expectation and Value also describe the switching criteria and visual attention allocation of drivers (Horrey et al., 2006). With all of these descriptions of driver adaptation, the general expectation is that drivers would look to the road more frequently when roadway demands increase, making it possible to maintain vehicle control and awareness of the driving environment even while performing a secondary task.

Although effective adaptation can reduce the risk of distraction to some degree, visual distraction caused by off-road glances still severely degrades drivers' performance and increases crash risk because the demands of the roadway are unpredictable (Lee, Regan, & Young, 2009). Looking away from the road at any time for even a short duration might incur a degree of risk. Visual distraction might diminish awareness for the roadway environment, making drivers less able to respond to evolving roadway demands in a proactive manner and making them less able to accommodate unexpected events. Poor awareness may also undermine drivers' ability to adapt glance patterns to the roadway demands. Thus, distraction-related crash risk may stem from a cumulative effect of many glances away from the road and the associated degradation of the drivers' awareness of the driving environment (Figure 16), or it may depend on only the current glance. The degree to which the history of glances contributes to crash risk has not been determined compared to the risk associated with the eyes simply being off the road at a given moment. Therefore, indentifying glance patterns that are most indicative of crash risk is the primary objective of this study.

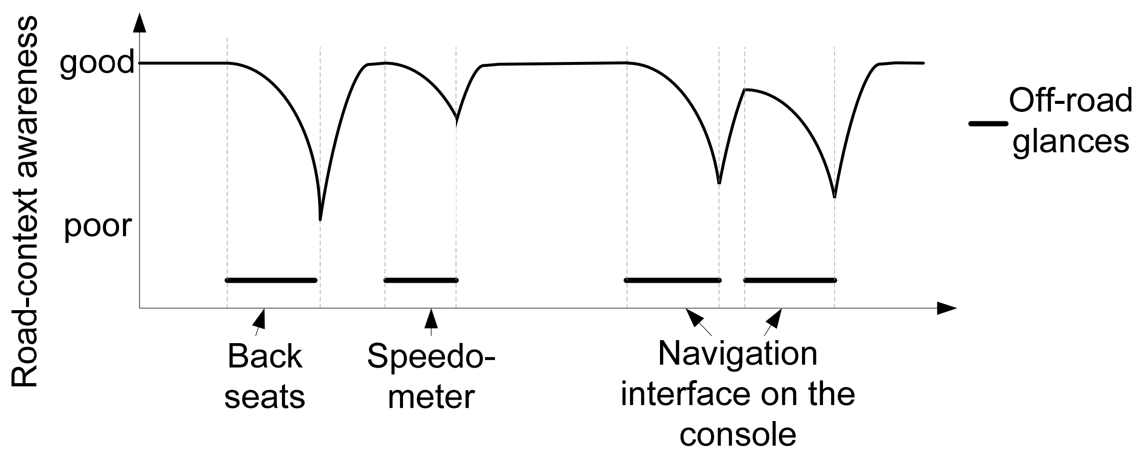


Figure 16. Drivers' awareness of the road context during the alternation of on- and off-road glances.

In the context of this study, visual distraction can be defined as a pattern of glances indicative of increased crash risk. Three characteristics of driver eye glance patterns can define visual distraction: duration, history, and location of eye glances. Long off-road glances caused by secondary tasks may be particularly detrimental. The longer the duration of a glance, the greater the delay a driver will incur in responding to an event that occurs during the glance. In addition, drivers may lose the awareness of dynamic driving context while looking away from the road; and this loss may accumulate during the glance in a non-linear fashion (Figure 16).

Beyond the effect of glance duration, the history of glances away from the road may also contribute to visual distraction, specifically the frequency of glances. Even short off-road glances might increase crash risk if they occur frequently. Frequent glances might undermine awareness of the road because drivers' awareness may not fully recover during a glance to the road before the eyes again move away from the roadway. The last two off-road glances in Figure 16 provide an example of the potential relationship between eye glance patterns and awareness. Such frequent glances can occur when drivers are engaged in the secondary task that requires many glances, such as entering an address into a navigation system or searching for a song in a long playlist. One un-explored issue is the length of glance history that should be considered in estimating visual distraction. One study that developed an algorithm to identify cognitive distraction found that a relatively long history of behavior (i.e., 30-40 seconds) was appropriate (Liang, Reyes et al., 2007). However, visual distraction may operate with a different time constant and may have more immediate effects. The crash risk associated with visual distraction may rise and fall quickly as the eyes are shifted toward and away from the road.

The third characteristic of eye glance patterns is the eccentricity of glance location relative to the roadway. The further away from the road a driver looks, the more it may increase crash risk. Focal and ambient vision both contribute to vehicle control, with focal vision playing a critical role in event detection and ambient vision supporting lane-keeping (Summala, Nieminen, & Punto, 1996). When drivers look away from the road, they can perceive the objects and detect motion outside visual focus with ambient vision (Horrey & Wickens, 2004a), but the resolution of objects in ambient vision is severely limited. That is, even when drivers are looking away from the road center, they may perceive the outline of the roadway and their movement relative to the road with ambient vision and so they may be able to maintain lane position and vehicle control with glances that do not diverge too much from the forward view. Focal vision is required for event detection, and so response to braking vehicles and traffic signals may be degraded with the eccentricity of glance location. In an instrumented vehicle study, glance eccentricity was inversely related to drivers' ability to maintain an adequate safety margin following a lead vehicle: the minimum time to collision decreased as drivers glanced further from the road (Lamble, Laakso, & Summala, 1999). Therefore, the eccentricity of eye glances may also affect crash risk.

<u>Quantifying distraction associated with glance patterns</u>

Based on the three characteristics of eye glance patterns, several approaches have been developed to estimate visual distraction as a function of eye glance patterns (Donmez et al., 2007; Engström & Mårdh, 2007; Senders et al., 1967; Wierwille & Tijerina, 1998; Zhang et al., 2006). Table 6 shows some typical approaches that consider the three characteristics of glance patterns.

Senders et al. (1967) described the effects of glances away from the roadway in terms of uncertainty about the driving environment. The study strictly controlled the duration of glances away from the road way, which diminished drivers' ability to adapt to driving situation. The equation in Table 6 shows that the uncertainty grows according to the 1.5^{th} power of the occlusion duration, which was demonstrated to be more sensitive to distraction than the linear relationship in the study integrating multiply datasets recording real crashes (Wierwille & Tijerina, 1998). This approach assumes that drivers' uncertainty depends only on the duration of the current glance away from the road.

In the initial analysis of the data from the 100-Car Study, the total off-road glance duration in the six-second interval was used to estimate distraction (Klauer et al., 2006) (Table 6). The interval was defined so that the precipitating event occurred in the fifth second. The results showed that total off-road glance duration less than two seconds did not increase the odds of crash/near crash events, but the risk doubled when the duration was greater than two seconds. This approach considered a history of six seconds and total duration of eye glances. Another estimate of distraction was developed for a system to warn drivers of their distraction (Donmez et al., 2007; Donmez et al., 2006). This algorithm used a weighted combination of the current off-road glance duration and the total off-road glance duration during the previous three seconds (Table 6). The threshold for non-salient warning was two seconds and 2.5 seconds for salient warning when α in the equation was set to 0.2. Similar to the 100-Car Study, this algorithm considered a history of glances, but it also included the momentary duration of the current glance away from the road.

Several studies have quantified driver eye-glance patterns to guide the design of in-vehicle systems. The results of these studies also suggest algorithms to detect visual distraction. A recent study combined duration, history, and eccentricity of off-road glances to estimate the total visual demands of a task (Engström & Mårdh, 2007) (the fourth approach in Table 6). The visual demands were described as the summation of the product of the 1.5th power of duration and a penalty for eccentricity of the glance relative to the road center for each off-road glance. The influence of eccentricity of a glance was derived from data showing that drivers' reaction time increases as the eccentricity of the glance increases (Lamble, Kauranen et al., 1999). A similar summation of off-road glances occurring in a time window was used to quantify visual distraction to support a lane-keeping assistant system (Pohl, Birk, & Westervall, 2007). This approach is integrates all three characteristics of eye glance patterns. In general, considering more glance features that have a clear relationship to driving performance should provide a more sensitive indicator of crash risk.

Table 6. Combination of duration, glance history, and glance eccentricity used to estimate visual distraction

<table>
<tr><th>Distraction estimate</th><th>Duration of eye glances</th><th>History of eye glances</th><th>Eccentricity of eye glances</th></tr>
<tr><td>1. Current glance duration (GD)</td><td>$U(t) = H \cdot D\left[1 - e^{-\left(\frac{V}{D}+\frac{1}{F}\right)t}\right] + K_n V^2 t^{1.5}$
where U is driver uncertainty, t is visual occlusion duration, H is the road information density (bit/mile), D is the decreasing weights of the information based on the distance to the vehicle, V is the speed of the vehicle, F is time constant of forgetting rate, and K_n is a scale (Senders et al., 1967).</td><td>Not considered</td><td>Not considered</td></tr>
<tr><td>2. Cumulative glances (CG)</td><td colspan="2">Total off-road duration in the 6 second window with the event occurring at the 5th second (Klauer et al., 2006)</td><td>Not considered</td></tr>
<tr><td>3. Cumulative glances current duration (CGCD)</td><td colspan="2">$Risk = \alpha \cdot \beta_1 + (1-\alpha)\beta_2$
where β_1 is current glance duration away from road during the last three seconds, β_2 total glance time away from road in the last three seconds, and α represented the weights of β_1 and β_2 on crash risk (Donmez et al., 2007).</td><td>Not considered</td></tr>
<tr><td>4. Cumulative glances, Current duration , and glance eccentricity (CGCDGE)</td><td colspan="3">$VD = \sum_i^N g_i^{1.5} \cdot E(\alpha), \qquad E(\alpha) = 6.5758 - \frac{1}{0.06\alpha+0.152}$
where N is the total number of off-road glances required by an in-vehicle task, g is duration of the off-road glances, E is penalty function of eccentricity, and α is radial gaze angle between the forward roadway and the display (Engström & Mårdh, 2007).</td></tr>
<tr><td>5. Buffered current glance duration and cumulative glances (Buffer)</td><td colspan="3">The level of buffer decreases immediately as a linear function of time with coefficient of one when driver looks outside the “field relevant for driving” (FRD) that are off-road and driving related glances (mirrors or speedometer). When driver looks back to the FRD (on-road glance) the buffer level increases as a linear function with factor of one but there is a 0.1 sec latency phase (adaptation phase) for the off-road glances and 1 sec latency phase for on-driving glances. During latency phase the buffer level remains at the current position before increasing.</td></tr>
</table>

Another approach to integrating the effect of glances over time is to define a buffer (the fifth approach in Table 6). This algorithm included a buffer of two seconds that defines the driver as distracted only after the driver looks outside the “field relevant for driving” (FRD) for more than two seconds. When the buffer is goes to zero, the driver is considered distracted. The algorithm considers three types of glances: on-road, driving related (mirrors or speedometer), and off-road glances integrated over time through a series of calculation rules (Table 6).

Although the approaches in Table 6 provide possible solutions to quantify the relationship between glance patterns and visual distraction, they have been neither compared with each other nor validated using naturalistic driving data. This study used the Naturalistic 100-Car Study data to compare these approaches and establish what characteristics of driver eye glance behavior influence the risk of crashes and near crashes. Such information could provide valuable contributions to developing real-time estimates of driver distraction that can support adaptive safety systems and other distraction countermeasures.

Methods

The 100-Car Naturalistic Driving Study data

The naturalistic 100-Car Study data were used in this study because they could directly connect distraction estimation with the risk of crashes in real driving, which makes the results of this study more generalizable to the design of distraction mitigation systems in real world. The data contained two databases: event and baseline. The event database included 69 crashes and 761 near-crashes, 830 in total. Crashes occurred when subject vehicles had any contact with other vehicles, humans, objects, and animals, and near-crashes described a conflict situation requiring a rapid, severe evasive maneuver to avoid a crash. These crash/near-crash events were identified from the continuous data by filtering with post-hoc "triggers" (Klauer et al., 2006). The post-hoc triggers used either single (e.g., any lateral acceleration value greater than ±0.6 g) or multiple (e.g., forward TTC value > 3 seconds plus a longitudinal deceleration value > -0.5 g) performance signatures to identify time points when drivers were likely to be involved in a crash or near-crash. These criteria resulted in a miss rate of less than 10% and false alarm rate less than 30%. Based on the criteria, data reductionists watched 90-second video for each event (60 seconds before and 30 seconds after) and recorded the nature of the event, driver's behavior prior to the event, and the surrounding environment. The event database contained vehicle kinematic data, eye glance data, and the state of surrounding objects from 30 seconds before the event until 10 seconds after the event.

The baseline database of 10,008 epochs was created using the case-crossover sampling method. The case-crossover method identified baseline epochs for each crash/near-crash event so that the baseline epochs had the same driver, similar time of day (±2 hours), same type of day (weekday/weekend), and a similar GPS location/relation to junction as the corresponding event. A maximum of 15 control epochs were identified for each event. Each epoch contained 30-second data in the same format as that in the event database.

The two databases formed a natural classification situation. However, the crash/near-crash events were caused by various reasons, and so only those events in which the driver was at fault were used in this analysis. Driver "at fault" events were defined as those where the driver was involved in some type of inattention to the road and this involvement represented a contributing cause of the event. Therefore, the data contained two classes: one is the crash/near-crash events in which the driver was at fault and another is the baseline epochs. There were some epochs in both databases that had missing eye glance data. Consistent with the previous analysis, events and baseline epochs were eliminated from the database if the glance data in the six-second period (from five seconds before to one second after precipitation factor) were missing or if the driver was not at fault (Klauer et al., 2006). These criteria for crashes and near crashes reduced the events from 829 to 687; and the criteria for baseline epochs reduced the total number from 10,008 to 8010. The criterion for considering only crashes and near crashes where the driver was at fault further reduced the number of events to 359.

The 100-Car Study collected a variety of variables describing driver behavior and state, vehicle state, and environmental situation. A data dictionary was used to organize these variables and to describe their relationships (Figure 17). In this dictionary, the variables were categorized at different levels of functional abstraction and aggregation over time. The functional abstraction classified the variables as the outcome (i.e., the goal of analysis), general description, and detailed variables. Temporal aggregation presented time granularity of the variables (i.e., the time scales of variables). It included epoch-based, period-based, and continuous, in which the data were aggregated by event/epoch, a time window, and sampling frequency. The continuous data were collected at 10 Hz, and the period-based data were obtained by summarizing the continuous data across time windows, which included 3, 6, 12 and 24 seconds. The variables of interest of this study included continuous eye-glance data, drivers' engagement in secondary tasks, and the environmental situation.

Algorithm development for visual distraction

Three categories of algorithms derived from the previous studies were implemented and three previously developed algorithms were replicated (Table 7). The derived algorithms considered different characteristics of glance patterns over different time periods, and the replicated algorithms were used as references for the performance of the derived algorithms. One of important characteristic of the algorithms was the definition of off-road glances. Except for the "Ongoing-history-linearbuff", all algorithms defined off-road glances as when drivers were not looking at the forward roadway.

The derived algorithms compared the importance of three characteristics of glance patterns: duration, history, and eccentricity. The algorithms used either linear or 1.5^{th} power of glance duration to quantify distraction associated with the duration of a glance away from the road, indicated as "-line" and "-1.5" in Table 7.

Temporary Aggregation

Functional Aggregation

Functional Aggregation		(Long) Epoch-based (aggregated by events)	Period-based (aggregated across a window size)	(Short) Continuum (raw data in collection frequency)
(Abstract)	Out-come	• **Event type**	• Crash risk	• Crash risk
	General description	• Driver activities • Vehicle state • Driving environment • Other vehicle activities • Statement	• Driver eyeglance pattern • Driving performance • Environment factors	• Driver instantaneous eyeglance • Driving performance • Environment factors
(Concrete)	Variables	• **Incident type** • **Pre-incident maneuver** • **Maneuver judgment** • **Precipitating event** • **Driver reaction** • **Post maneuver control** • **State and action of associated vehicles** • **Driver impairment** • **Driver distractions** • **Driver hands on the wheel** • **Vehicle factors** • **Visual obstructions** • **Road surface condition** • **Traffic flow** • **Travel lanes** • **Traffic density** • **Traffic control/Junction** • **Roadway curvature/ Alignment** • **Road type** • **Lighting** • **Weather** • **Seatbelt**	• Percent of road center • Mean off-road glance duration • Mean on-road glance duration • Average eccentricity of glances • Throttle hold • Average throttle position • Lateral acceleration error • lateral acceleration reversal rate • Average lateral acceleration • RMS of longitudinal acceleration • RMS of speed • RMS of vehicle heading • Mean of traffic demand rating	• **Eye glance indicator** • Duration of current glance • **Gaze location** • **Throttle** • **Brake** • **Yaw** • **Vehicle heading** • **Lateral acceleration** • **Longitudinal acceleration** • **Vehicle speed** • **Turning signal** • **Range of nearby objects** • **Range rate of nearby objects** • **Azimuth of nearby objects** • Traffic demand rating

The bolded indicate the variables that can be obtained directly.

Figure 17. Data dictionary of variables related to calculating crash risk associated with glances away from the road.

Table 7. The algorithms to estimate distraction level based on eye glance patterns

Algorithms	Current glance duration	Glance history	Eccen-tricity
1. Ongoing-nohistory $VD(t) = \begin{cases} 0, & \text{on\_road} \\ f(t - T_n), & \text{off\_road} \end{cases}$ $VD(t)$ is the level of visual distraction at time t, and T_n is the time when the n[th] glance that is off-road glance starts.	**-1.5** $f(t - T_n) = (t - T_n)^{1.5}$	No	No
	-Linear $f(t - T_n) = t - T_n$	No	No
	-Ecc $f(t - T_n) = (t - T_n)^{1.5}\, E(\alpha)$ E is the eccentricity penalty for off-road glance location. $E(\alpha) = \begin{cases} 0.39, & \text{Ellipse I} \\ 1.12, & \text{Ellipse II} \\ 2.02, & \text{Ellipse III} \end{cases}$	No	In E
2. Ongoing-history $VD(n,t) = V(n-1, T_n) + f(t - T_n)$ $VD(0,t) = 0$ $VD(n,t)$ is the level of visual distraction at time t when the n^{th} glance happens, $f(t - T_n)$ is the distraction the n^{th} glance at time point t, and T_n is the time point of the onset of the n^{th} glance.	**-1.5** $f(t - T_n) = \begin{cases} -(t - T_n)^{1.5}, & \text{on\_road glances} \\ (t - T_n)^{1.5}, & \text{off\_road glances} \end{cases}$		No
	-Linear $f(t - T_n) = \begin{cases} -(t - T_n), & \text{on\_road glances} \\ t - T_n, & \text{off\_road glances} \end{cases}$		No
	-Ecc $f(t - T_n) = \begin{cases} -(t - T_n)^{1.5} E(\alpha), & \text{on\_road glances} \\ (t - T_n)^{1.5} E(\alpha), & \text{off\_road glances} \end{cases}$ E is the eccentricity penalty for off-road glance location.		
3. Summation-window size (3, 6, 12, 24 sec) $VD = \sum_i^N f(t_i)$, $f(t_i)$ is the distraction of the i^{th} off-road glance, N is the total number of off-road glances during a time window, and t_i is the duration of the i^{th} off-road glance	**-1.5** $f(t_i) = t_i^{1.5}$		No
	-Linear $f(t_i) = t_i$		No
	-Ecc $f(t_i) = t_i^{1.5} \times E(\alpha)$ E is the eccentricity penalty for the glance location.		
4. Cumulative Glance (CG)	Total off-road glance duration in six seconds. Events: the six seconds include five seconds prior to and one seconds after the instant of the event. Baseline epochs: it is the last six seconds in the epochs.		No
5. Cumulative Glance Current Duration (CGCD) (3, 6, 12, 24 sec)	$VD = 0.2\beta_1 + 0.8\beta_2$ β_1 is current glance duration away from road and β_2 total glance time away from road in the current time window.		No
6. Buffer (Ongoing-history-linearbuff) $VD(n,t) = V(n-1, T_n) + f(t - T_n)$ $VD(0,t) = 0$, $VD(n,t)$ is the level of visual distraction at time t when the n^{th} glance happens, $f(t - T_n)$ is the distraction the n^{th} glance at time point t, and T_n is the time point of the onset of the n^{th} glance.	$f(t - T_n) = \begin{cases} -(t - T_n - T_{delay}), & \text{FRD glances} \\ (t - T_n), & \text{off\_road and on\_drive glances} \end{cases}$ $T_{delay} = \begin{cases} 1 \text{ sec when back from off\_road glance} \\ 0.1 \text{ sec when back from on\_drive glance} \end{cases}$ where FRD "field relevant for driving" glance - intersection of visual angle of 90 degrees and the car windows; on_drive glance – glances at mirrors or speedometer.		In T_{delay}

For glance history, only "ongoing-nohistory" category did not consider history of eye glances. Among the algorithms considering glance history, there were two ways to set the length of history to consider. One, implemented in "ongoing-history" category, was to consider the entire epoch and calculating the level of distraction as continuous accumulation or dissipation of distraction. Off-road glances led to increments and on-road glances led to decrements of distraction. In this way, the distraction decreased to or stayed at zero when drivers looked at the road for a relatively long time; and the distraction increased when drivers looked away from the road. Another approach, implemented in "summation-window size" categories, was to consider a fixed length of glance history by summarizing glances over a fixed time period, which was defined by the window size. The size of the time window can be critical. If the size is too small, the algorithms might not capture the cumulative effect of eye glances on distraction level. But if the window is too big, the influence of recent glances could be diluted by the glance behavior of the distant past. The window sizes considered were 3, 6, 12, and 24 seconds.

The influence of glance eccentricity was tested by including it in the algorithms labeled "-Ecc". Eccentricity of eye glance location was calculated based on the equation developed by Engström et al. (2007). Because the radial gaze angle from the road center was not available in the 100-Car data, we used three ellipses to quantify the eccentricity of off-road glances, which were also used in the previous report of the 100-Car Study (Klauer et al., 2006) (Table 8 and Figure 18). The effect of eccentricity of each ellipse was calculated by averaging the influence of visual angle in the range of that ellipse. The contributions to the visual distraction calculation are 0.39 for the Ellipse I, 1.12 for the Ellipse II, and 2.02 for the Ellipse III.

Table 8. Glance eccentricity division (Klauer et al., 2006)

	Average visual angle	**Glance locations**
Ellipse I	Less than 20°	Left forward, right forward, instrument panel
Ellipse II	20°~40°	Center mirror, radio/HVAC, left mirror
Ellipse III	Greater than 40°	Left window, right mirror, right window, passengers in right-hand seat, hand-held device, object/other, eyes closed

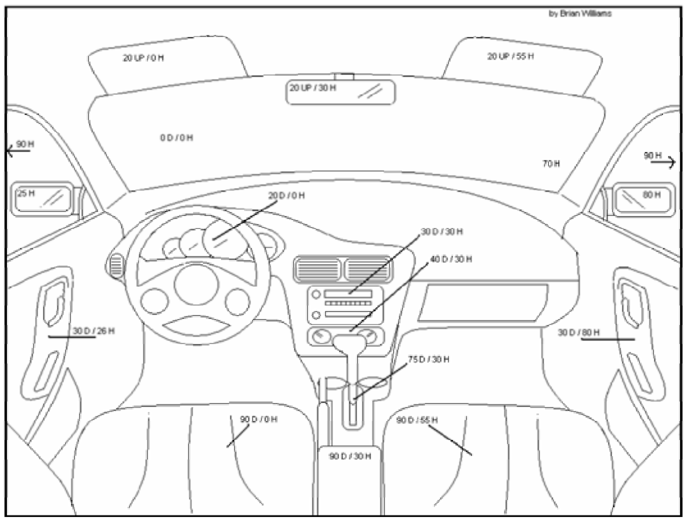


Figure 18. Depiction of degrees of visual angle, as measured from center forward view, of objects in cockpit of an automobile (Klauer et al., 2006).

We also replicated three kinds of algorithms developed in literature. The "CG" algorithm was developed in the 100-Car Study report (Klauer et al., 2006) and used as the standard to compare with the other algorithms. The CGCD algorithm developed by Donmez (2007) integrated both the cumulative effect of glances and the effect of the current duration of glances. The third replicated algorithm, the 'buffer ' algorithm, which defined glances in terms of glances to the forward roadway, driving-related glances away from the forward roadway, and glances not related to driving. All three algorithms considered duration in a linear fashion to calculate distraction level. "CG" and "CGCD" considered a fixed time period in considering the history of glances and did not consider the eccentricity of glances while the “buffer algorithm” considered cumulative distraction across the whole course of glance history.

Algorithm evaluation

The algorithms were evaluated by assessing how well the calculated value of visual distraction indicated an increased risk of a crash or near-crash event. The algorithms each produced continuous estimates of visual distraction over each of the baseline epochs and each of the crash or near-crash events. The crash risk associated with the level of visual distraction at the end of the baseline epochs and at the point of the precipitating event in the crash and near-crash events was compared using an odds ratio analysis. The odds ratio indicates how much likely a crash is to occur when distraction is above a particular level compared to when it is not.

Because each algorithm produces an estimate of distraction on a different scale, the level of distraction must be normalized for comparison. The levels of distraction were defined by dividing the distribution of distraction for the event and baseline epochs into 20 segments of five percentiles each, ranging from zero to 100. The odds ratios and their 95% confidence interval were calculated using logistic regression for each of these segments, as shown in Figure 19a. Dividing the distribution of distraction by the percentiles, hereafter called percentile division, ensures that the odds ratios of different algorithms could be compared. For some algorithms, the value ranges bounded by the lower percentiles (e.g., 5th, 10th percentiles) were combined because the value of these percentiles was identical, which was caused by highly skewed distribution of distraction. For instance, Figure 19a shows the odds ratios for an algorithm and Figure 19b shows the distribution of distraction produced by that algorithm. The distribution of distraction is highly skewed to the left, and the estimated distraction is zero in the lowest 30th percentiles. Therefore, the levels of distraction below 30 percentile were combined for this algorithm. If no levels were combined, then the odds ratio was calculated for 20 levels of distraction for each algorithm. When the odds ratio of a level was greater than one (i.e., its 95% confidence interval was beyond one), distraction at that level leads to an increased crash risk relative to baseline driving.

We assumed that high distraction value led to high crash risk. A good algorithm was expected to produce a steep, monotonic relationship between odds ratio and distraction level, as shown in Figure 19. This study used linear regression models to describe this relationship. The dependent variable of the regression model was the odds ratio, and the independent variable was the level of distraction. The slope of the regression models indicated how quickly the odds ratio increased with distraction level: the larger the slope, the faster odds ratio increased. The R-square of the regression models indicated how well the data fit this linear monotonic relationship. Besides the regression model, the maximum odds ratio was used to describe the highest crash risk that the algorithm could indicate. The underlying assumption of this analysis is that the odds ratio reflects the accuracy with which distraction is estimated: a good algorithm will have a high odds ratio when distraction is high and a low odds ration when distraction is low.

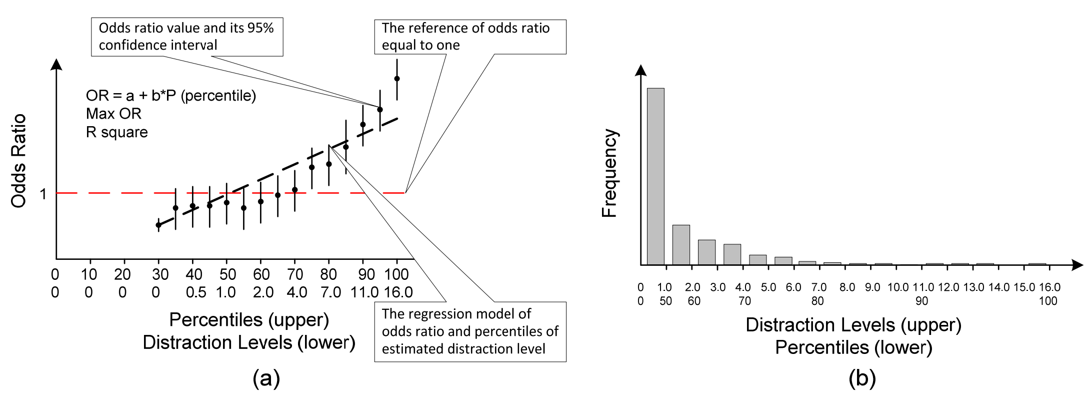


Figure 19. The changes of the odds ratio with distraction level in the percentile division.

The odds ratio can be calculated according to the contingency table (Table 9) or logistic regression. However, this approach can evaluate the odds ratio of crash risk for only one factor at a time. Being more flexible, logistic regression can integrate multiple factors into one model. This benefit of the logistic regression is that it can identify the relative contributions of other factors to the odds of a crash/near-crash event. The logistic regression uses the logit function, the natural logarithm of the odds of events happening, to transform a binary dependent variable to a continuous one. Then, the regression procedure determines the best fitting linear combination of independent variables for the logit of the binary variable:

$$logit\ p = ln\frac{p}{1-p} = A + BX \qquad (5)$$

where p is the probability of crashes/near-crashes happening, X ($X_1, X_2, X_3, \ldots X_k$) is the set of independent variables, and A and B ($B_1, B_2, \ldots B_k$) are intercept and regression coefficients. In this study the binary dependent variable was events/baseline epochs, and independent variables were estimated distraction level and other related factors of crash risk. The odds ratio can be calculated based on the fitted logistic model:

$$OR = \prod_{i=1}^{k} e^{B_i} \qquad (6)$$

Table 9. The equation to calculate odds ratio.

	In the interested range	Out of the interested range
Crash/near-crash events	a	b
Baseline epochs	c	d
The equation to calculate odds ratio: $OR = \frac{ad}{cb}$		

Note: a,b,c, and d are counts of the epochs belong to the corresponding category.

Results

Cumulative glance duration and crash risk

The “CG” algorithm performed in a manner consistent with the results of the analysis in the 100-Car Study (Klauer et al., 2006). Similar to the previous report, the odds ratio of crashes/near-crashes was at least two, statistically greater than one, for the total time eye off-road (TTEOR) greater than two seconds (Table 10). However, the current results showed slightly higher odds ratio than those in the previous report. Shown in Table 10, the odds ratio for TTEOR from one to two seconds were marginally greater than one, which was less than one in the previous study; and the odds ratio of TTEOR greater than two seconds in the current analysis (OR: 2.61) was also slightly greater than that in the previous report (OR: 2.19). In addition to the odds ratios from zero to two seconds, we also calculated the odds ratios for one-second segments, ranging from two to six seconds (Figure 20). The increasing trend of the odds ratio with TTEOR could be approximately fitted in a straight line, indicating the odds ratio increases in a linear manner up to six seconds.

Table 10. The odds ratio and 95% confidence interval of total time eye off-road (TTEOR)

Total time eye off-road (TTEOR)	Current results			Previous results (Klauer et al., 2006)		
	Odds Ratio	Lower CI	Upper CI	Odds Ratio	Lower CI	Upper CI
<=0.5 sec	0.47	0.38	0.59	1.31	0.91	1.89
0.5~1.0 sec	0.75	0.54	1.03	0.82	0.60	1.13
1.0~1.5 sec	1.37	1.00	1.88	0.92	0.65	1.31
1.5~2.0 sec	1.41	0.98	2.02	1.26	0.89	1.79
>2.0 sec	**2.61**	**2.06**	**3.29**	**2.19**	**1.72**	**2.78**

To compare “CG” with other algorithms (Table 2), the odds ratio was also calculated according to the percentile division (CG in Figure 21). The “CG” plot in

Figure 21 shows the odds ratio started to be greater than one from the 85th percentile that was 2.20 seconds. The regression model had a moderate slope (0.028), and this model could explain 71% of variance of the odds ratios. The maximal odds ratio was 3.23 for the 95th to 100th percentiles (3.50~6.00 seconds).

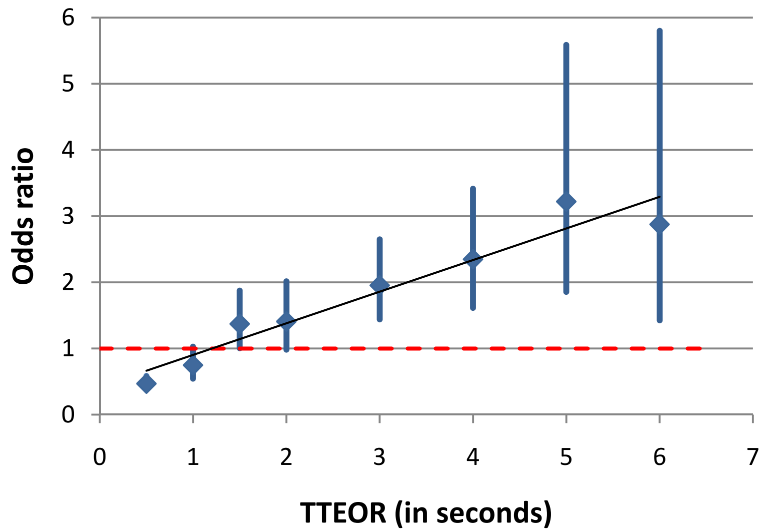


Figure 20. The odds ratio changes with total time eye off-road (TTEOR).

Effect of glance history, duration, and eccentricity on crash risk

For all derived algorithms, the odds ratio for the crash/near-crash events increased with the estimated visual distraction (Figure 21). This increasing trend described by a linear regression model showed that the derived algorithms describe drivers' eye glance patterns in a way that indicates crash risk. The comparisons between the derived algorithms help to identify the best way to describe drivers' eye glance patterns to estimate visual distraction. The estimation parameters include slope and R-square of the linear regression models and maximum OR are directly compared (Figure 22 and Table 11).

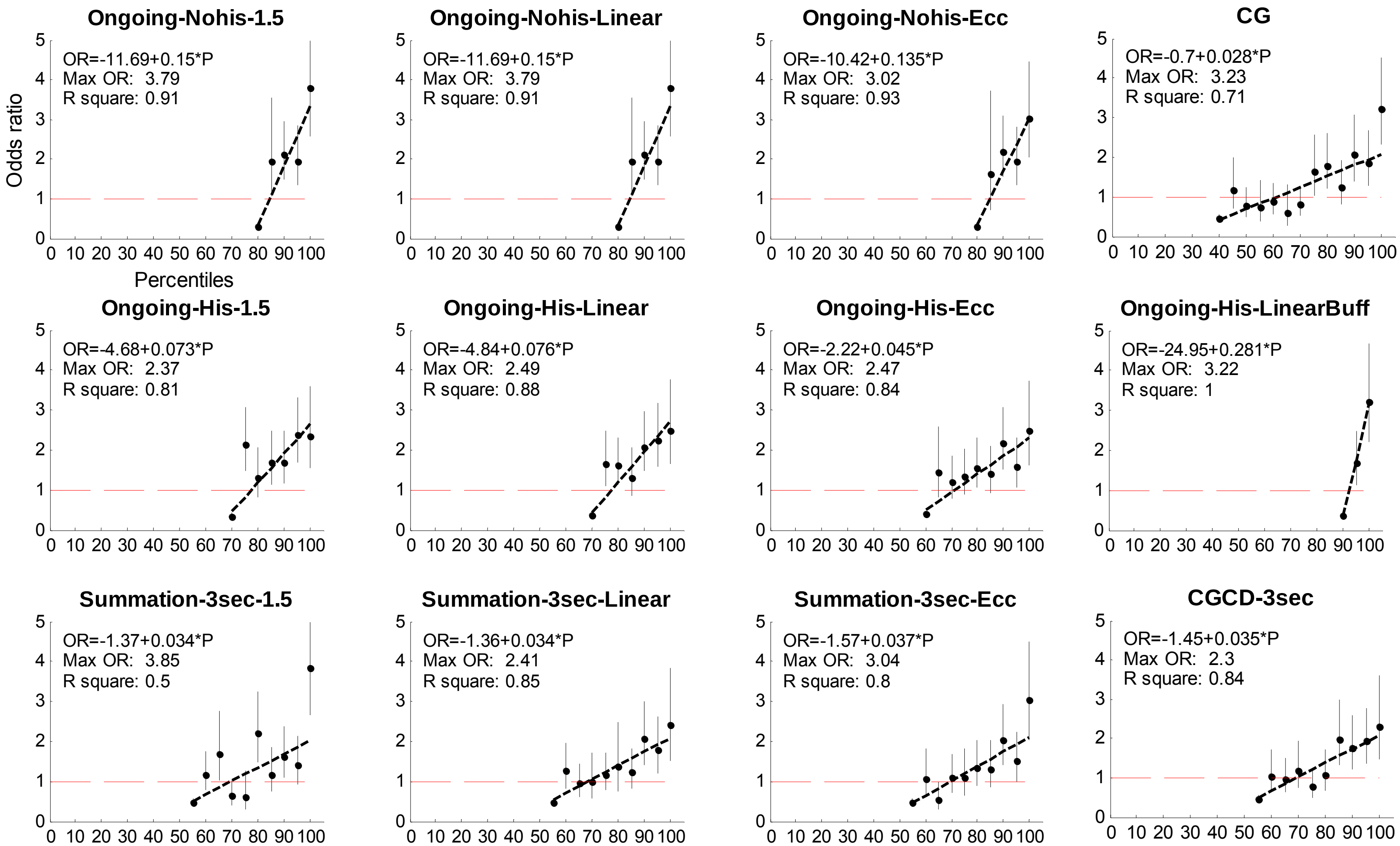


Figure 21. The odds ratio for crash/near-crash events associated with 24 methods for estimating distraction

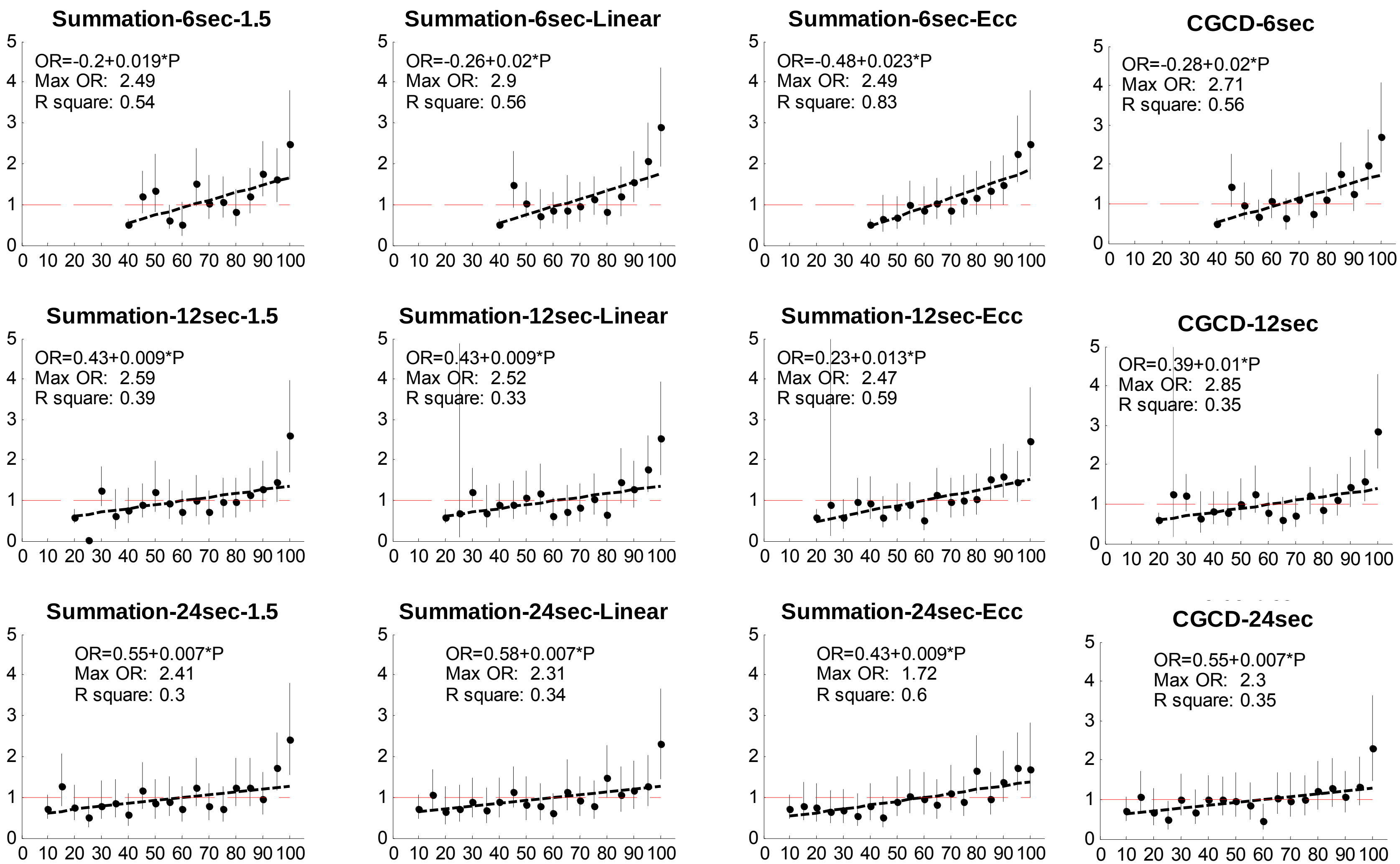


Figure 21 continued

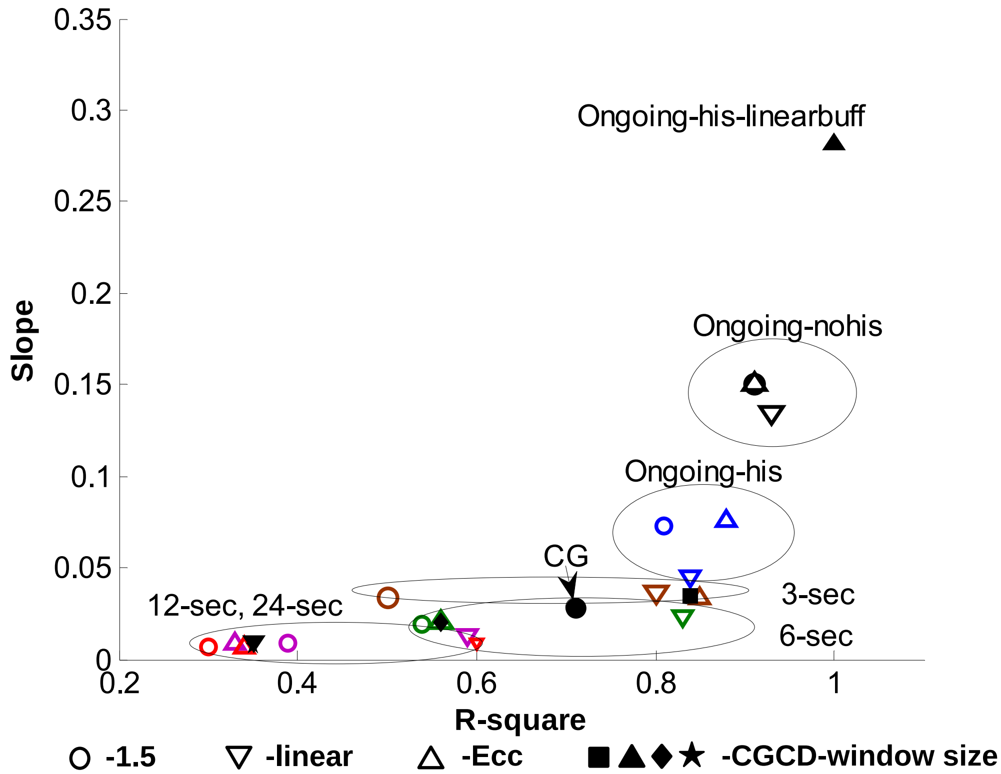


Figure 22. The comparison of the estimation algorithms for visual distraction. The size of marks indicate maximum odds ratio

The comparison showed that 1.5th power of glance duration did not significantly improve the estimation of visual distraction, which was demonstrated in Figure 22 and Table 11. The slope and R-square for the algorithms using 1.5th power of eye glance duration were not always higher than those using a linear contribution of the duration (Figure 22). Similar results occurred for maximal odds ratio (Table 11). These results suggest that the 1.5th power and the linear influence of the duration are similar when indicating crash risk.

Similar to the 1.5th power of duration, considering glance history was not beneficial for identifying crash risk either. The comparison between the algorithms of

“Ongoing-history” and “Ongoing-nohistory” showed that the odds ratio for the algorithms that did not consider history –“Ongoing-nohistory”— increased faster, were fit better by a linear model, and produced larger maximal odds ratios than the algorithms considering history (Figure 21, Figure 22 and Table 11).

Table 11. The performance parameters of the estimation algorithms for visual distraction

Algorithms	**Slope**	**R-square**	**Maximum OR**
Ongoing-nohistory -1.5	0.15	0.91	3.79
Ongoing-nohistory -Linear	0.15	0.91	3.79
Ongoing-nohistory -Ecc	0.135	0.93	3.02
Ongoing-history -1.5	0.073	0.81	2.37
Ongoing-history -Linear	0.076	0.88	2.49
Ongoing-history -Ecc	0.045	0.84	2.47
Summation-3sec-1.5	0.034	0.5	3.85
Summation-3sec -Linear	0.034	0.85	2.41
Summation-3sec -Ecc	0.037	0.8	3.04
Summation-6sec-1.5	0.019	0.54	2.49
Summation-6sec -Linear	0.02	0.56	2.9
Summation-6sec -Ecc	0.023	0.83	2.49
Summation-12sec-1.5	0.009	0.39	2.59
Summation-12sec -Linear	0.009	0.33	2.52
Summation-12sec -Ecc	0.013	0.59	2.47
Summation-24sec-1.5	0.007	0.3	2.41
Summation-24sec -Linear	0.007	0.34	2.31
Summation-24sec -Ecc	0.009	0.6	1.72
CG	0.028	0.71	3.23
CGCD-3sec	0.035	0.84	2.3
CGCD-6sec	0.02	0.56	2.71
CGCD-12sec	0.01	0.35	2.85
CGCD-24sec	0.007	0.35	2.3
Ongoing-history-linearbuff	0.281	1	3.22

The direct comparison of the algorithms that used the summarized eye glance measures across different window size ("Summation-window size") showed that a small window size led to better algorithms than a large window size (Figure 22). The slope of the regression models decreased with the increase of window size (Figure 22). These results showed that longer window led to worse estimates of visual distraction.

The eccentricity of off-road glances did not improve the estimation of visual distraction. The comparison between the algorithms labeled as "-1.5" and those with "-Ecc" (Figure 21) showed that the slope and R-square of the regression models, and maximal odds ratio were similar (Figure 22 and Table 11). These results indicate that the eccentricity of off-road glances also did not improve crash risk estimation. Summing up the comparisons, the algorithms that used an instantaneous measure of glance duration and did not consider glance history (e.g., "Ongoing-nohistory") were the most precise indicators of distraction-related crash risk.

Compared with the derived algorithms, the "CG" algorithm produced a very similar pattern of odds ratios as the algorithms of "Summation-6sec" (Figure 21), which is not surprising because both algorithms summarized eye glance measures over a 6-second window size. Nonetheless, compared with the instantaneous off-road glance duration ("Ongoing-nonhistory") — the most indicative measure of crash risk—the estimated distraction of the "CG" algorithm led to relatively small changes in the odds ratio as distraction increased.

"CGCD" used the combination of ongoing off-road glance duration and summarized off-road glance duration in a time window as inputs. The change in the odds over levels of distraction for this category of algorithms was very similar to the algorithms of "Summation-window size" when using the same window size (Figure 21). This similarity showed that the estimated distraction by "CGCD" was the glance behavior summarized over the window, while the term associated with the ongoing off-road glance duration did not affect the distraction estimation much. It suggests that giving more weight to the ongoing input term might improve the performance of algorithms that combined both cumulative glance information and current glance duration.

Although "Ongoing-history-linearbuff" obtained the highest slope and R-square, 90% of the distraction estimates were zero and only three values of the odds ratio were involved in the calculation of regression evaluation measures, which suggests that the slope and R-square of the regression model may not be suitable to evaluate the performance of "Ongoing-history-linearbuff". This discrepancy between this algorithm and the other algorithms results from the different ways to define off-road glances. "Ongoing-history-linearbuff" included three types of glances: FRD (on-road, field relevant for driving), on-drive, and off-road, and FRD and on-drive glances contained the area of the intersection of visual angle of 90 degrees, the car windows, mirrors, and speedometer. But, other algorithms included only on-road and off-road glances. It implies that the definition of eye glances is an important parameter in the estimation of crash risk.

Discussion

In this study, six categories of estimation algorithms of visual distraction, which included "CG" used in the previous report of the 100-Car Study (Klauer et al., 2006), were examined based on the 100-Car naturalistic data set. The results show the eye glance patterns can indicate drivers' visual distraction and crash risk. The algorithms considering the instantaneous changes of off-road glance duration produce the best estimation of visual distraction, which is sensitive to crash risk. Unexpectedly, none of the factors expected to correspond to crash risk associated with glances, 1.5^{th} power of glance duration, glance history, or eccentricity of glance location, significantly improved the algorithms.

This study replicated the previous analysis of glance cumulative glance duration on crash risk (Klauer et al., 2006). The results were compared with the previous results and the current analysis obtained a slightly higher odds ratio than the previous one. This discrepancy may be caused by the different sampling methods of two baseline databases: case-control for previous study and case-crossover for this study. Case-crossover baseline epochs matched the crash/near-crash events with specific driver and environment factors (i.e., location, time of day, and day of week) while the case-control database was randomly sampled and proportional to only the number of the events occurring with vehicles. Thus, the case-crossover methods provided a better match between crashes and baseline and excluded the potential confounding caused by these environment factors and drivers when estimating the contribution of visual distraction to crash risk.

The algorithm comparisons show that visual distraction depends on the instantaneous changes of off-road glance duration, which is consistent with the explanation of how off-road glances impair driving performance described in Figure 16. Once looking away from the roadway, drivers lose track of the roadway situation and their distraction level increases, which leads to high crash risk. Nonetheless, most studies use eye glance measures that are summarized over time, but not the instantaneous changes of off-road glance duration, to estimate visual distraction (Donmez et al., 2007; Engström & Mårdh, 2007; Klauer et al., 2006). The results of this study suggest that summarizing driver eye glance activities across a period of time dilutes the signal of distraction by averaging it with non-indicative behavior.

The algorithm comparison shows that the 1.5^{th} power of off-road glance duration did not improve the estimation of visual distraction. Nonetheless, in two previous studies the 1.5^{th} power of off-road glance duration produced more accurate estimation of drivers uncertainty or total visual demand of a secondary task than the duration itself (Senders et al., 1967; Wierwille & Tijerina, 1998). This discrepancy between the current and previous studies may be caused by the characteristics of the specific dataset and different research purposes. This study used the 100-Car dataset that recorded driver behavior in actual driving situations and distraction was gauged by the risk of collision. In contrast, Senders et. al (1967) used the data collected in on-road experiments that had more control on both eye-off-road time and driving environment. They used vehicle velocity to reflect drivers' uncertainty with the assumption that drivers would adapt their velocity proportionally to their uncertainty about driving environment, which might not be accurate due to different individuals' reaction to absence of visual information. Moreover, their analysis focused on the continuous changes of driver uncertainty, but not discrete crashes. Although the analysis by Wierwille and Tijerina (1998) used real-driving data and crash risk, they were interested only in the aggregated association between visual demand of secondary tasks and frequency of crashes. Moreover, they did not use real-time eye movement data to assess eye glances, and their datasets came from different sources, which might not be obtained in a consistent situation. Therefore, our analysis with a single naturalistic dataset (the 100-Car data), suggests that the 1.5th power and linearity of glance duration do not differ substantially in predicting crash risk.

As with the 1.5th power of glance duration, the eccentricity of glance location did not improve the estimation of visual distraction. Some studies report that when drivers look at the places close to the road center, their ambient vision can support visual perception of the roadway in some degree (Horrey & Wickens, 2004b). Although the ambient vision may help drivers to maintain an acceptable, but degraded, lane-keeping, the absence of the focal vision on the roadway can result in serious impairment on hazard perception and lead to crashes. Although some other studies argue that eccentricity of glance location does matter when estimating distraction level (Engström & Mårdh, 2007; Pohl et al., 2007), the results of this study do not support this assertion. Moreover, a reliable indicator of on-road and off-road glances can be more easily obtained in real driving than the eccentricity of glance location.

Although the comparison between "Ongoing-nohistory" and "Ongoing-history" shows that glance history is not necessary in distraction estimation, a short period of previous glance behavior may be still important. Based on the observation, frequent, even short, off-road glances indeed impair driver performance (Liang & Lee, In revision). However, this impairment may be so slight as to not have a substantial effect on crash risk. One reason for this outcome is that the historical glance pattern is not as detrimental as single long off-road glance and only leads to a crash in situations with high driving demands. These rare situations might not be included in the 100-Car dataset. However, such a situation can be conveniently implemented in a driving simulator, with which researchers can control both driving demands and visual demands of secondary tasks. A future study might test whether glance history is important for visual distraction estimation under different driving demands in simulator experiments.

Compared with the derived algorithm, "CG" had a similar performance to the algorithms using the summarized eye glance measures across six seconds as inputs, but was outperformed by the algorithms using the instantaneous changes of off-road glance duration. These results again demonstrate that modeling instantaneous changes of driver eye-glance behavior presents a promising way to estimate visual distraction.

Like discussed earlier, short cumulative effects of off-road glances, as well as instantaneous changes of glance activities, may be important for distraction estimation. "CGCD" seems to provide a solution by combining both ongoing off-road glance duration and summarized total off-road glance duration. But the results of the algorithms were very similar to those only using summarized inputs ("Summation-window size"), showing that the CGCD algorithm placed too much emphasis on the accumulative effects of eye glance patterns. To improve this algorithm, it is critical to identify the appropriate balance between instantaneous and accumulative effects of off-road glances and an accurate deterministic period of the accumulative effects in the estimation of visual distraction.

The results of this analysis suggest that visual distraction detection requires only one indicator—duration of off-road glances— and focuses on instantaneous effects of eye glances. The results suggest any degraded awareness that might accumulate as a result of a prolonged period of glances to and away from the road had little effect on crash risk. This contrasts with the detection of cognitive distraction which is best done by integrating many performance indicators (e.g., driving performance, eye gaze and eye glance measures) across a relative long period of time (e.g., 30 seconds). These differences have important implications for detecting distraction: cognitive and visual distraction need different algorithms and sensors. This study showed the algorithm and sensors needed for detecting visual distraction can be quite simple. The need for two systems of distraction detection depends to some degree on the overall risk posed by each type of distraction.

Conclusions

Visual distraction estimated by analyzing drivers' eye glance patterns can indicate crash risk. Visual distraction estimated by the algorithms considering the instantaneous changes of off-road glances is the most indicative to crash risk. Unexpectedly, some variables of eye glance patterns including 1.5th power of glance duration, glance history, and eccentricity of glance location did not improve the algorithms. In contrast to previous chapter in which algorithms developed to detect cognitive distraction were based on simulator data, this chapter used naturalistic driving data from the 100-Car Study, which enable us to connect distraction estimation with the risk of crashes.

This and the previous chapters studied the detection of visual distraction and cognitive distraction, but two types of distraction usually occur in combination for most in-vehicle secondary tasks (e.g., entry an address into a GPS system). In these situations, the effects of visual demands and cognitive demands may interact and algorithms that independently detect visual and cognitive distraction might not perform well. Therefore, it is important to understand the interaction of visual and cognitive demands and to detect combined distraction based on the interaction. Nonetheless, the difficulty of identifying instances of cognitive distraction in the naturalistic data makes hard to study combined distraction in a systematic manner. The following chapter presents an experiment that examines the effect of visual and cognitive distraction alone and in combination and describes a sequential strategy to detect the various combinations of distraction.

CHAPTER V. INVESTIGATING THE INTERACTION OF VISUAL AND COGNITIVE DISTRACTION AND DETECTING THE COMBINED DISTRACTION

In real driving situations, visual distraction and cognitive distraction typically occur simultaneously and interact to affect driver behavior. In some situations, such as conversations, cognitive distraction predominates. In others, such as tuning the radio it is visual distraction. However, most have a combination of various levels of visual and cognitive distraction, such as with text messaging. Chapter VI demonstrated that visual distraction makes an important contribution to crash risk. However, the contribution of cognitive demands of secondary tasks to crash risk has not been estimated. Moreover, the detection for the combined distraction should be tailored to the interaction of visual and cognitive distraction, and no study has developed the detection algorithms for this situation.

This chapter investigated the combined effects of two types of distraction and tested a sequential strategy that jointed the detection algorithms developed in Chapter III and VI to identify the combined distraction. This used a simulator experiment to systematically manipulate cognitive and visual distraction and measure their effect on driving performance. A simulator experiment was conducted to examine the effects of visual, cognitive and combined distractions and to evaluate a sequential strategy to detect the different types of distraction. The sequential strategy first identified the presence of visual distraction and then detects cognitive distraction. It was hypothesized that visual distraction will dominate the effects of cognitive distraction when both types of distraction occur simultaneously and that the combined distraction was more detrimental than visual distraction. The sequential detection strategy was proposed based on these hypotheses.

The results show that when two types of distraction occur in combination, visual distraction dominates the effects of distraction on driver performance. Inconsistent with the original hypothesis, combined distraction is less detrimental than visual distraction; and cognitive distraction actually dilutes the effects of visual demands, reducing the overall effect on driving performance. To detect the combined distraction, the effective approach is to detect visual distraction first and then detect cognitive distraction only when visual distraction does not occur

<u>The effects of visual, cognitive and combined distraction</u>

Although visual distraction and cognitive distraction both interfere with driving, their effects on driver behavior are different. First, visual distraction and cognitive distraction degrade driving performance through different mechanisms. Visual distraction diverts drivers' visual attention, and cognitive distraction withdraws information processing resources from the driving task. Based on Multiple Resource Theory (MRT), visual distraction interferes with the driving task more than cognitive distraction because visual distraction competes for resources critical for driving. Second, there are overt behavioral indicators of visual distraction, such as looking away from the road, whereas the effects of cognitive distraction are much more subtle (Table 1).

Copy of Table 1. Effect of driver distraction on performance measures compared to normal driving

	Visual distraction	**Cognitive distraction**	**Combined distraction**
Eye activities	high frequency of off-road glances, long total eye-off-road time, and low percentage of road-center	gaze concentration in the center of the road	high frequency of off-road glances and long total eye-off-road time gaze concentration when drivers look at the road
Lane position	large lane variation	unchanged or small lane variation	large lane variation
Steering control	discrete steering correction and large correct magnitude (large steering error)	small correction magnitude (small steering error)	discrete steering correction and both large and small correct magnitude (>5°)

In the combined situation, the two types of distraction interact to influence driver behavior. The potential effects of their interaction can be described by the scale depicted in Figure 23. One possible interaction is that the effects of one type of distraction completely overshadow the other. Another possibility is that the effects of combined distraction are similar to the sum of visual distraction and cognitive distraction. Different interactions between visual and cognitive distraction suggest that the detection algorithm for one type of distraction may be unsuitable to detect the distraction in the combined situation. Therefore, understanding the interaction of visual and cognitive distractions is critical for developing algorithms to detect driver distraction.

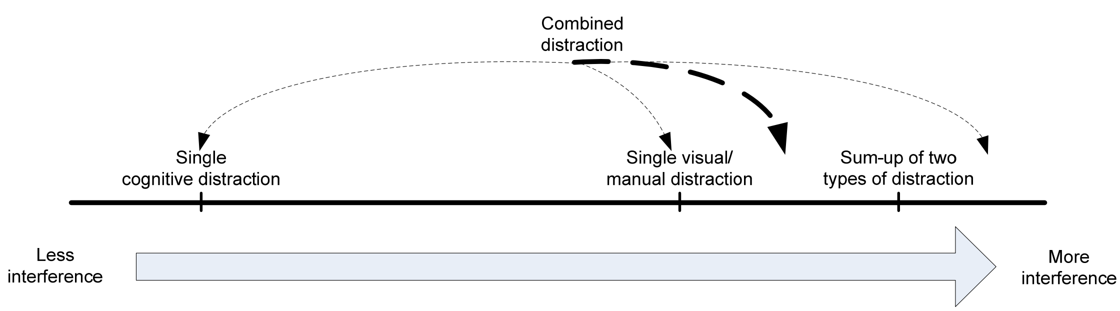


Figure 23. The scale of interaction between two types of distraction in the combined situation.

The hypothesized interaction is that that visual distraction dominated the effects of distraction when both types of distraction occurred simultaneously and that combined distraction would be more detrimental than visual distraction because of cognitive demands. The combined distraction may result in similar performance impairment as single visual distraction, but with longer off-road glances, larger variability of lane position and more abrupt steering control because the additional cognitive demands might impair drivers' ability to manage their engagement in the distraction task (shown by the bold dashed arrow in Figure 23). Table 1 presents hypothesized effects of the combined distraction on driver behavior.

Methods

A simulator experiment compared vehicle lateral control, hazard detection, and visual behavior before, during, and after secondary tasks that pose visual, cognitive, and combined distraction. The experiment used a driving simulator to reproduce essential elements of roadway demands and a simulated in-vehicle information system to reproduce demands representative of navigation systems.

Participants

Sixteen healthy volunteers (eight male and eight female) were recruited to participate the experiment. They were native English speakers, had normal or corrected-to-normal vision, possessed a valid U.S. driver's license for at least five years, and were between 35 to 55 years old with a mean of 45 and standard deviation of 6.3. Participants were compensated for their time, and a bonus was offered as an incentive for performing the secondary tasks.

Experimental design

The experiment used a 4(distraction) x 3(task phase) within-subject design. Four levels of distraction included driving with no distraction, with visual distraction, with cognitive distraction, and with combined visual and cognitive distraction. The distraction—visual, cognitive and combined—was implemented by the secondary tasks that reflected the visual and cognitive demands representative of navigation systems. Participants completed eight eight-minute drives; each drive contained one distraction level; and each distraction level was replicated twice, one level in two drives. The order in which the participants received these levels was counterbalanced, and the same sequences were used for male and female participants. The task phases described three time periods that divided the drive into the periods before, during and after the secondary task: a one-minute pre-task period, six-minute task period, and one-minute post-task period. Only in the task periods did participants perform the secondary tasks. In the no-distraction condition, the phases matched to the time period in which the driver would have otherwise performed the task and the three task phases simply reflected the beginning, middle, and end of the drives.

Apparatus and driving environment

The experiment took place in a fixed-base, medium-fidelity driving simulator. A rear-projection screen with 768 x 1024 resolution located approximately 2 m in front of the drivers produced a driving scene that spanned approximately 50 degrees of visual field. The simulator collected data at 60 Hz. A faceLab™ eye tracking system by Seeing Machines (version 4.1) collected eye movement data at 60 Hz. This system collected blink frequency and horizontal and vertical coordinates for a gaze vector that intersected the simulator screen. The simulator was also equipped with a seven-inch LCD touch screen mounted on the right side of the dash to generate the in-vehicle interface. The screen displayed color images in 640 x 480 resolution and was placed approximately 25 degrees laterally and 20 degrees vertically below drivers' line of sight.

The roadway used in this experiment was a straight, five-lane suburban arterial roadway comprised of two lanes in each direction separated by a center turning lane. All traffic lanes were 3.66 meters wide. Traffic in the left lane approached the subject vehicle (SV) from behind and traveled 10 mph (16kph) faster than SV, with spacing between cars of 3-6 seconds apart. Participants were instructed to drive at 45 mph (72kph). SV was equipped with a simulated cruise control system to ensure that the participants maintained a constant velocity. The cruise control was automatically activated when the vehicle reached 45 mph (72kph). A chime indicated the activation of the cruise control, and participants could deactivate the system by pressing the brake. Participants were encouraged to use the cruise control system as much as possible.

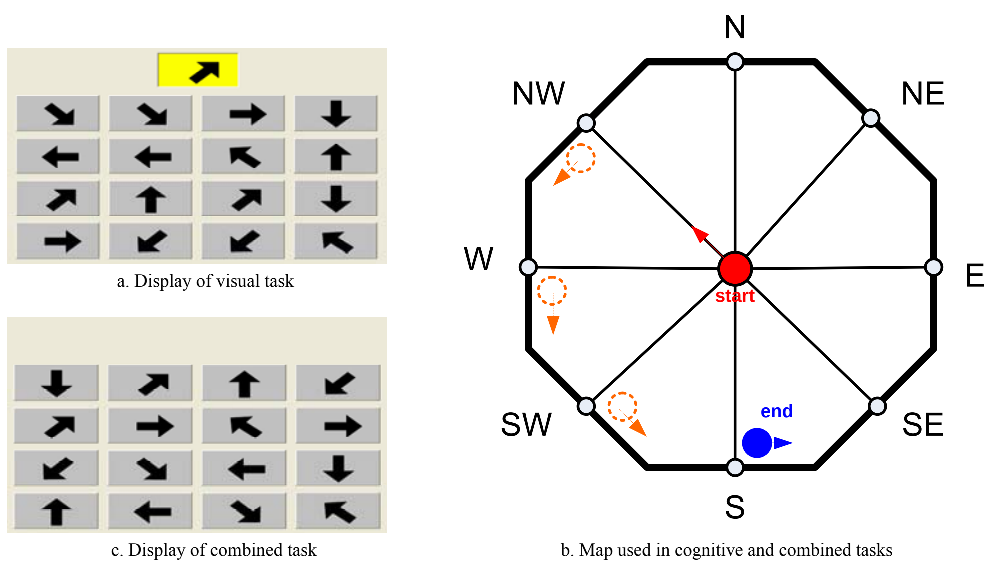
Throughout the drives, a lead vehicle (LV) was coupled to the SV by a 1.8-second tailway. The LV braked periodically, which required a rapid response from participants to avoid collisions. Five braking events occurred in each drive at a random time; approximately four events occurred in task phase and one in the pre- or post-task phases. A vehicle in the left traffic lane pulled in front of the LV to provide the cue of the onset of the brake event, which likely shortened the reaction time of attentive drivers. When there was no braking event, no vehicle in the left traffic would pull out. The tailway between LV and SV was decoupled with the onset of the braking and the LV braked at 0.2 g with the brake lights on until it reached a minimum speed of 20 mph (32kph) or until the participant had braked. During braking events, the cruise control was disabled when the participants pressed the brake pedal. Following a brief, random delay (0 to 5 seconds) the brake lights of the LV turned off and the vehicle accelerated at 0.25 g until it reached 25 mph (40kph). After the braking event, the LV was again coupled to the SV with a 1.8-second tailway.

A continuous external disturbance forced the vehicle toward the lane boundary, requiring participants to remain vigilant to the lateral position of the vehicle. The force would push the vehicle over of the lane boundary in five seconds if steering was neglected. The direction of this force changed every 6 to 11 seconds according to a uniform random distribution.

In-vehicle tasks

Distraction was manipulated using three in-vehicle secondary tasks, which simulated visual and cognitive demands of navigation and other complex in-vehicle information systems. The visual secondary task was inspired by the HASTE studies (Engström et al., 2005) and simulated the visual and manual demands associated with interpreting maps and other visually complex displays. Participants looked to the display (Figure 24a) and selected an arrow in a 4x4 matrix to match the target on the top of the display.

The cognitive secondary task simulated the spatial processing of navigation, and it required participant to listen to audio clips describing the path of a person and then verbally identify which cardinal direction (e.g., east, north, and southwest) that this person faced at the end of the path. The traversed the garden shown in map in Figure 24b. The garden had eight stations connecting to the center. The participants were told to consider travelling to one of the stations from the center, turned clockwise or count-clockwise, and then travel to the nth station. An example task was: “Go to northwest station, turn count-clockwise. Which direction is the person facing when walking to the third station?” The answer would be east. This task simulated the extreme of cognitive demands that drivers might face in processing direction information from navigation systems.



a. Display of visual task

c. Display of combined task

b. Map used in cognitive and combined tasks

Figure 24. In-vehicle displays of the visual and combined tasks and map of the garden in the cognitive task

During the combined task, the participants listened to audio clips similar to those in the cognitive task and selected the orientation using the interface similar to the visual task. In this task, the audio clips of cognitive task were divided into two parts. After each part of the message, participants identified the orientation using the touch screen display (Figure 24c). For example, after "go to northwest station, turn count-clockwise" was played, the message stopped and participants selected an arrow representing the orientation of the person using the touch screen. Then another part was played, "which direction is the person facing when walking to the third station", and participants responded again. This task combined the demands of the visual and cognitive tasks in a sequential way.

The timing of the three tasks was the same: the participants had five seconds to respond. If they responded in less than five seconds, another task would follow immediately. Otherwise, the next task would begin after five seconds. In this way, the participants were constantly distracted by the secondary tasks during the six-minute task period.

The terms visual and cognitive distraction provide an imprecise indication of the demands associated with the secondary tasks in this experiment. A GOMS description more precisely defines the secondary task demands (Table 12). Although the tasks shared some common resource demands, the visual task imposed primarily visual demands, cognitive task imposed primarily spatially-coded information processing demands, and combined task imposed both visual and spatial-coded information processing demands.

Table 12. The GOMS models of the three in-vehicle tasks and the resource required by the tasks

Visual task (Primarily visual demands)

- Goal: select the arrow to match the target
  - Goad: read the target
    - Move the eyes to the target (V)
    - Memorize the direction of the arrow (C)
  - Goal: search the correct arrow in the option array *repeat until finding the matched arrow*
    - Move the eyes to one of arrow the array (V)
    - Recognize the direction of the arrow (V)
    - Read the target again *if forgetting its direction* (V, C)
    - Match the directions (C)
  - Goal: press the button
    - Lift the right arm (M)
    - Point to the arrow (V, M)
    - Press the button (M)

Cognitive task (Primarily spatial-coded information processing)

- Goal: identify the final orientation of the person
  - Goal: identify intermediate direction *repeat until the message is finished*
    - Identify the initial direction (C)
    - Listen to a section of the message (A)
    - Rotate the orientation mentally according to the section of the message (C)
  - Goal: speak the final direction (C)

Combined task (Primarily visual perception and spatial-coded information processing)

- Goal: select the arrow indicating the final orientation of the person
  - Goal: identify intermediate direction *repeat until the message is finished*
    - Identify the initial direction (C)
    - Listen to a section of the message (A)
    - Rotate the orientation mentally according to the section of the message (C)
  - Goal: search the correct arrow in the option array *repeat until finding the matched arrow*
    - Move the eyes to one of arrow options (V)
    - Recognize the direction of the arrow (V)
    - Match direction with the intermediate direction identified (C)
  - Goal: press the button
    - Lift the right arm (M)
    - Point to the button (V, M)
    - Press the button (M)

Note: V represents visual perception, A represents auditory perception, C represents spatial- and verbal-coded information processing, and M represents manual response.

Procedure

Upon arriving at the laboratory, each participant read the informed consent document and gave consent. Then, the participants sat in the vehicle, and the eye tracker was calibrated. Next, the participants learned to perform the in-vehicle tasks by listening to the instructions and then repeating the tasks until they could comfortably perform the tasks, based on self-report. This training took approximately 15 minutes. Participants then drove a 12-minute practice drive to familiarize themselves with the driving environment and LV braking events, during which participants drove four minutes and then practiced each kind of task for two minutes. Following the practice drive, participants completed eight experimental drives, each approximately eight minutes long.

The participants were told to drive safely and perform the in-vehicle tasks as they were able; that is, safe driving was told to be high-priority task. The participants did not receive any feedback regarding their driving or task performance during the experimental drives. The quality of eye tracking was monitored throughout the experiment, and the calibration was adjusted before each drive. At the end of experiment, participants completed a payment form and were debriefed concerning the purpose of the study.

Dependent variables

Table 13 summarizes the dependent variables that characterize drivers' vehicle lateral control, hazard detection, and visual behavior. Steering error and standard deviation of lane position characterize the lateral control performance of drivers. Steering error was calculated as the difference between the second-order Taylor series expansion prediction of steering angle and the observed steering angle (Nakayama et al., 1999). It measures the smoothness of steering control, and larger values reflect more abrupt control. Hazard detection was measured using the response to the LV braking events. Brake reaction time was the time from brake light illumination to participants pressing brake pedal. Eye glances, blink, and eye movements including fixations and saccades were used to characterize drivers' visual behavior. Fixations and saccades were identified using a previously developed algorithm (Liang, Reyes et al., 2007). All variables were summarized across 30-second time windows.

Table 13. The variables describing visual, lateral control and hazard detection behavior of drivers

Vehicle Lateral Control	**Visual behavior**
Steering error	Off-road glance duration
SD of lane position	Off-road glance frequency
	Blink frequency
Hazard (brake events) perception	SD of fixation horizontal position
Brake reaction time (BrakeRT)	SD of fixation vertical position
Minimal headway time (MinHWT)	Saccade speed

Results

The effects of driver distraction: Visual, cognitive, and combined

This study compared drivers' vehicle lateral control, hazard detection and visual behavior for four levels of distraction and three task phases. The statistical model was a within-subject ANOVA with repeated measures and implemented using the MIXED procedure of SAS 9.0 with the compound symmetry covariance structure and Tukey-Kramer post-hoc comparisons. The statistical comparisons are shown in Table 14.

Vehicle Lateral Control

Distraction levels, task phases, and their interaction all had a statistically significant effect on vehicle lateral control (Table 14). Figure 25 shows that the different distractions have little effect on the pre and post-task phases and the effect was largely limited to the task phase. Comparing types of distraction for only the task phase, the visual and combined secondary tasks resulted in significantly less smooth steering control and large variance of lane position compared to the baseline, and the visual task had a larger influence (Table 14). During the cognitive task drivers moved the steering wheel less smoothly than the baseline, but had smaller variability in lane position (Table 14). These results indicate visual distraction severely impairs vehicle lateral control. In contrast, cognitive distraction makes drivers' steering control more abrupt, but may improve lane-keeping performance.

Table 14. Statistical results of the comparisons

Statistical tests / Dependent variables	**Main effects and interaction**			**Post-hoc analyses of different distraction levels during task phase periods**					
	Distraction level	**Task phase**	**Interaction**	**V vs. B**	**Cog vs. B**	**Com vs. B**	**V vs. Cog**	**V vs. Com**	**Cog vs. Com**
	$F_{3,45}$	$F_{2,30}$	$F_{6,90}$	t_{90}	t_{90}	t_{90}	t_{90}	t_{90}	t_{90}
Steering error	24.26**	135.94**	36.55**	27.02**	3.02**	14.07**	23.85**	13.20**	-10.94**
SD of lane position	8.77**	5.03**	16.83**	14.20**	-3.60**	3.45**	17.63**	10.81**	-7.03**
BreakRT*	14.17**	n/a	n/a	5.53**	1.07	4.67**	4.30**	1.01	-3.43**
MinHWT*	12.00**	n/a	n/a	-4.84**	-1.56	-4.99**	-3.15**	0.02	3.25**
Off-road glance duration	17.29**	27.47**	31.06**	19.06**	-2.06**	13.63**	21.54**	6.50**	-16.05**
Off-road glance frequency	126.73**	192.96**	120.11**	50.72**	-0.64	22.26**	50.98**	28.85**	-22.74**
Blink frequency	7.36**	8.26**	5.44**	-2.61**	7.62**	6.75**	-10.07**	-9.24**	0.93
SD fixation X position	3.35**	29.22**	2.94**	-5.93**	-5.72**	-6.90**	-0.27	0.84	1.12
SD fixation Y position	13.89**	6.16**	0.95	-6.81**	-5.33**	-5.21**	-1.53	-1.70	-0.16
Saccade speed	6.05**	6.11**	1.37	-6.61**	-6.46**	-7.61**	-0.22	0.87	1.11

Notes: V, Cog, Com, and B indicate the estimated value of the measures under visual distraction, cognitive distraction, combined distraction, and baseline condition. * The post-hoc comparison tests of BrakeRT and MiniHWT are t_{45}, instead of t_{90}. ** The tests obtained significant difference at α=0.05.

The effect of task phase was investigated to assess the extent to which secondary tasks produce a persistent effect on driving performance. Comparing the pre-task and post-task periods, visual and combined tasks resulted in marginally or significantly rougher steering control in the post-task period (Visual: steering error: t_{90}=-1.91, p=0.06; Combined: steering error, t_{90}=-2.98, p=0.004), but cognitive distraction did not (t_{90}=-1.16, p=0.25). Comparing pre-task and post-task periods for lane-keeping performance shows that the baseline and combined distraction resulted in higher or marginally higher variance in the post-task period compared to the pre-task period (Baseline: t_{90}= -2.05, p=0.04; combined: t_{90}=-1.94, p = 0.06); the cognitive distraction resulted in lower lane variance in the post-task periods (t_{90}=2.09, p=0.04); the visual distraction resulted in similar lane variance in the post-task periods (t_{90}=-0.74, p=0.46). Comparing the periods before and after the tasks suggests some lingering effect for the combined task, but some of this effect may also reflect general fatigue or adaptation to the driving task as reflected in similar effects for the baseline condition.

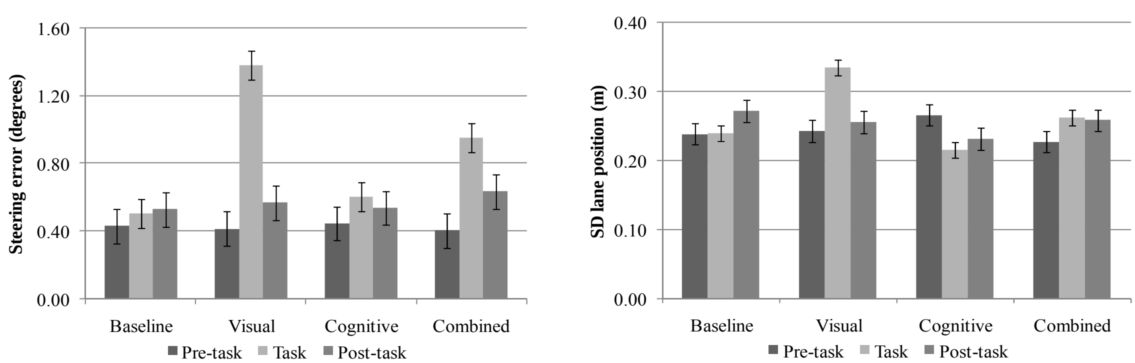


Figure 25. Drivers' vehicle lateral control performance.

Hazard Detection Associated with LV Braking Events

This analysis focused on drivers' performance during those braking events that occurred during the task period. The levels of distraction had a statistically significant effect on BrakeRT and minHWT (Table 14 and Figure 26). The visual and combined secondary tasks both increased reaction time to the events and reduced the minimum time headway compared to the no-task baseline condition, but cognitive distraction resulted in similar performance as the baseline (Table 14). These results suggest that visual distraction degrades hazard detection; but, contrary to previous findings, cognitive distraction failed to influence hazard detection performance in a statistically significant manner.

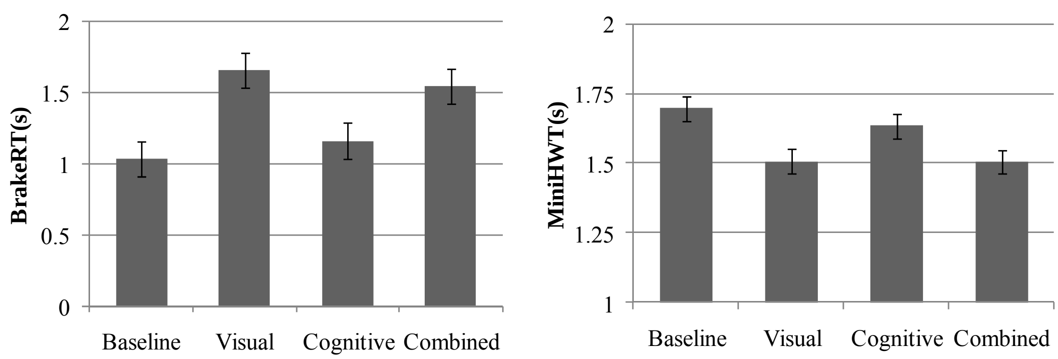


Figure 26. Hazard detection (LV braking event) performance.

Visual Behavior

The analysis of drivers' visual behavior focused on the pattern of eye glances away from the road, blink rate, and the distribution of fixations to the road. Eye glance patterns were described by off-road glance duration and frequency (Table 13). Not surprisingly, the visual and, to a lesser extent, the combined distraction resulted in longer and more frequent off-road glances compared to the cognitive distraction and baseline condition; the cognitive distraction resulted in even shorter off-road glances than the baseline condition (Figure 27 and Table 14). These effects are related to the changes in vehicle lateral control (Figure 27 and Figure 25).

Longer eyes-off-road time, as calculated by the product of off-road duration and frequency was associated with more abrupt steering control and larger lane variation, accounted for the influence of experimental conditions on driving performance. Fitting regression models to the data of individual drivers showed that, eye-off-road time explained 39% of variance in steering error and 17% of the variance in lane position variation. The experimental conditions accounted for a further 10% of the steering error variance and 6% of the lane position variation. This increase is not statistically significant for 6 of the 16 drivers when considering steering error and 10 drivers for lane position variation.

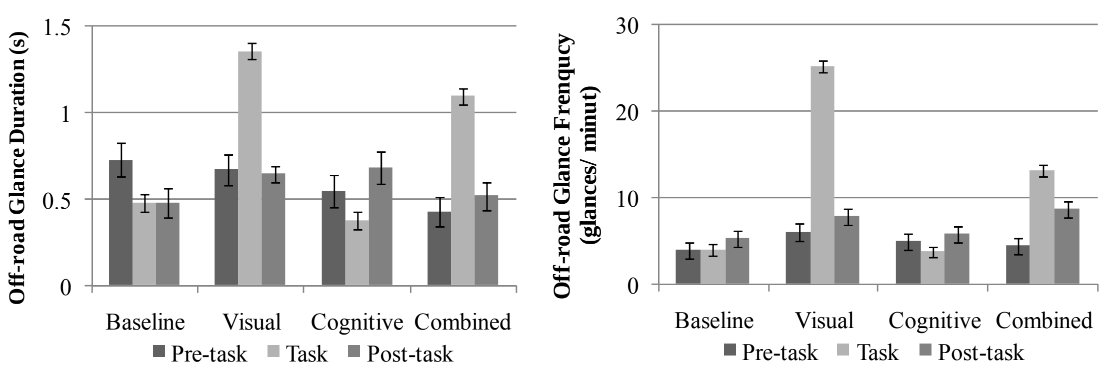


Figure 27. Eye glance patterns.

Figure 28a shows the cognitive and combined tasks led to a greater blink rate than the visual task and baseline condition. The blink rate increased after the visual task (V: task vs. post, t_{90}=3.79, p=0.0003), and remained high following the combined task (Com: task vs. post, t_{90}=-0.31, p=0.76), but decreased after the cognitive task (t_{90} =-2.52, *p*=0.01). These results suggest that blink frequency is a sensitive index of cognitive distraction and that extended periods of intense visual distraction have an influence that persists beyond the end of the task. Nonetheless, blink frequency explained only 4% of variance in steering error and 2% of the variance in lane position based on the data from all three secondary tasks. Compared with eye-off-road time, the relatively weak association of blink frequency with steering and lane maintenance suggests that the off-road glances, independent of the cognitive demands, are the primary source of the degraded steering control and lane-keeping, while increased blink frequency associated with cognitive demands is not.

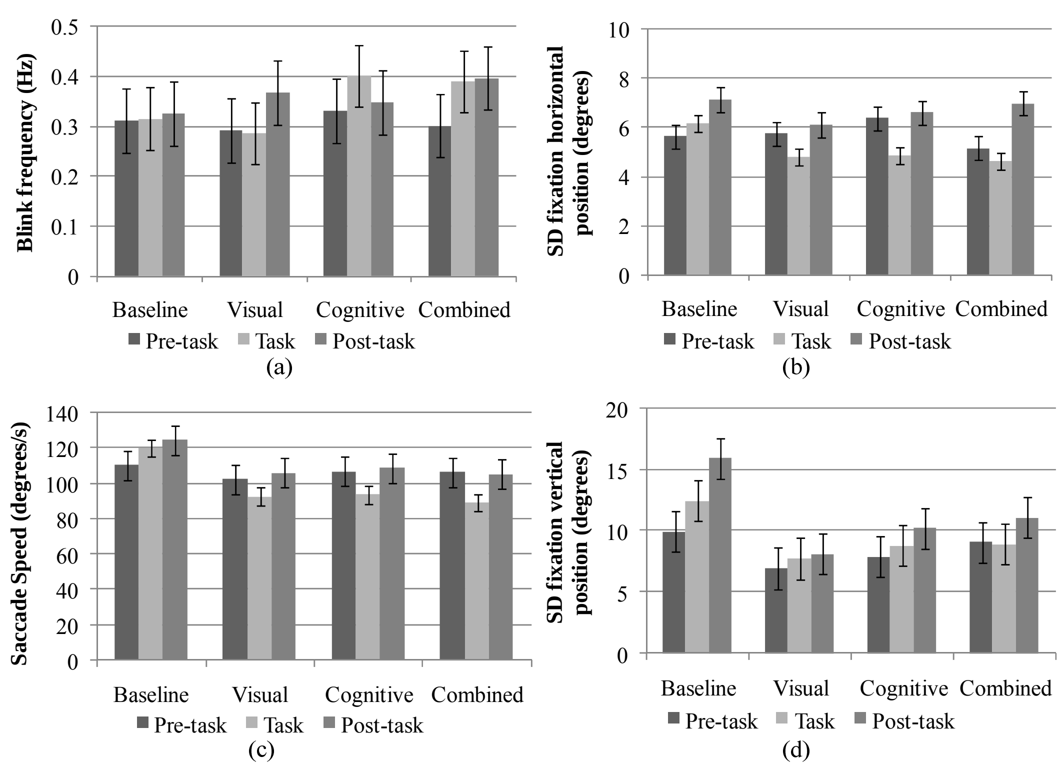


Figure 28. Blink frequency and eye movement patterns.

The distribution of drivers' fixations to the roadway became more concentrated in the all three distraction conditions, as reflected by the reduced standard deviation of the horizontal and vertical fixation location (Figure 28 b, d and Table 14). All three secondary tasks led to a vertical concentration of fixations across all three task phases—relative to the baseline condition, the vertical distribution of fixations was concentrated even in the pre and post-task phases. In contrast, the horizontal concentration was most pronounced during the tasks. Distraction slowed saccades across all three task phases, as with the vertical fixation concentration (Figure 28c and Table 14). These results suggest that not only cognitive but also visual distraction can disrupt the distribution of fixations when drivers look to the roadway. The product of standard deviation of the horizontal and vertical fixation location explained only 10% of variance in steering error and 5% of the variance in lane position based on the data from all three secondary tasks. This relatively weak association contrasts with the much stronger influence of eyes-off-road time on steering error.

Lane departure analysis

The lane departures were examined in detail to understand distraction-related control failures. The lane departure was defined as any part of the vehicle crossing the lane boundary, which corresponds to a deviation from the lane center of more than 1.06 meters. The lane departures during visual and combined distraction substantially outnumber those during cognitive distraction and baseline condition (Visual: 190, Combined: 61, Cognitive: 20, and Baseline: 10, χ^2_6=292.96, p<0.001). Based on inspection of plots of eye glance patterns and lane and steering wheel position before lane departures, three failure types leading to the lane departures were identified: steering neglect, under-compensation, and over-compensation. Figure 29 shows the eye glance and steering behavior from five seconds before to two seconds after a lane departure associated with a typical steering failure. The analysis of these failures helps identify how secondary tasks contribute to lane departures.

Steering neglect occurred when drivers failed to correct vehicle heading when the vehicle was drifting toward a lane boundary. This lane drift occurred when lane position and direction of lateral velocity were in the same direction, and persisted for several seconds preceding the lane departure. This type of failure often occurred when drivers looked away from the road center for a relatively long period and failed to notice the changes in the vehicle state.

Under-compensation occurred when drivers failed to adjust the steering sufficiently to direct the vehicle back to the road center when the vehicle had drifted towards the edge of the lane. With this type of failure, drivers usually looked to the road center, seemed to notice the vehicle drifting, and then adjusted the steering wheel, but the adjustment was insufficient.

Over-compensation was associated with rapid and repeated steering wheel movements, resulting in large swings in lateral velocity and lane position. Large, poorly-timed changes in the steering wheel angle were associated with frequent, but short off-road glances.

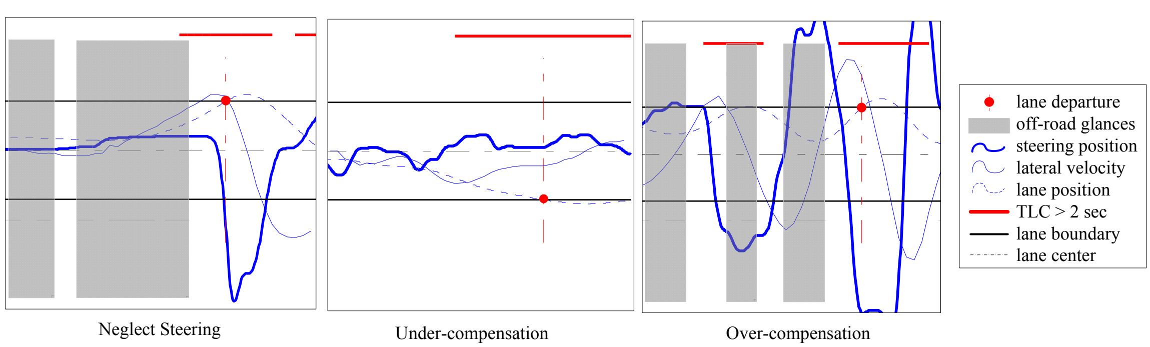


Figure 29. Typical examples of steering neglect, under-compensation, and over-compensation.

The subjective judgment that classified the three steering failures was verified using a logistic regression with three measures of steering patterns and two measures of driving performance (Table 15). These measures were calculated for the two seconds before lane departure. The most indicative measures were identified for each steering failure using a logistic regression with a stepwise greedy search, which makes local optimum choice in each step with the hope of finding global optimum (Table 15). The model for steering neglect used SP1, SP2, and TLC, and accuracy was 94% (hit rate 0.96, false alarm rate 0.21). The model for the under-compensation used SP2 and TLC, and the accuracy was 92% (hit rate 0.70, false alarm rate 0.02). The model for over-compensation used SP3 and STD-SP, and the accuracy was 89% (hit rate 0.67, false alarm rate 0.04). Table 15 and Figure 30 show how the logistic regression models formalize the subjective classification of steering failures.

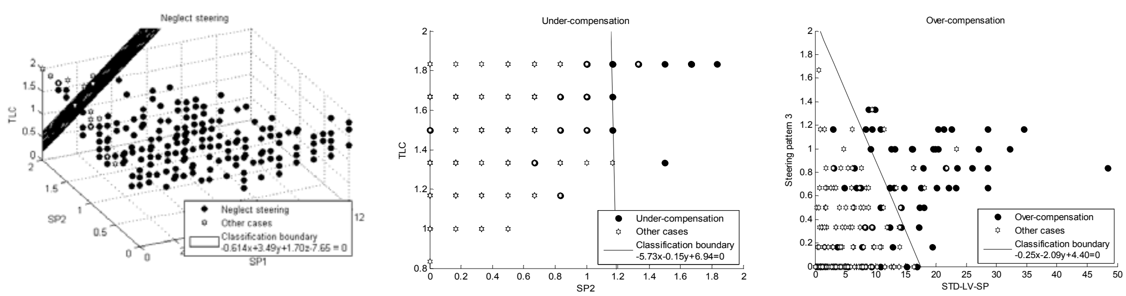


Figure 30. The decision boundary of the logistic models of three types of steering failure.

The three types of steering failure were differentially associated with the secondary tasks (Table 16). Steering neglect and over-compensation occurred most frequently during the visual and combined secondary tasks (Visual: 90%; Combined: 80%), but accounted for only 40% of the lane departures during cognitive task. In contrast, under-compensation represents 50% of the lane departures that occurred during cognitive task, but only 8% of those that occurred during the visual task and 16% during the combined task. These results suggest that primary mechanism leading to lane departures with the visual and combined tasks is similar. With the combined task, steering neglect and over-compensation contributed to most of the departures, but the proportion of under-compensation was higher than during the visual task. This confirms the general finding that visual distraction dominated the overall effect of combined distraction, but cognitive demands of the combined distraction had an influence.

Table 15. Quantify three types of steering failure

Measures	**Definition**
SP1	The duration when the associated conditions were met: steering position, lateral-velocity, and lane position error were in the same direction. In this situation drivers did not move the steering wheel to correct their heading when drifting.
SP2	The duration when the associated conditions were met: steering position was in the opposite direction of the lateral-velocity and lane position. In this situation drivers move the steering wheel to correct vehicle heading, but not sufficiently to compensate for the lane drift.
SP3	The duration when the associated conditions were met: lateral-velocity and lane position were in opposite directions. In this situation the vehicle moved toward the center of the road.
STD-SP	The standard deviation of steering position.
TLC	The duration when time-to-lane-cross was over 2 seconds.

Logistic models to quantify three types of steering failure:

Steering neglect:

$$\text{logit}(p) = 0.61 \times \text{SP1} - 3.49 \times \text{SP2} - 1.70 \times \text{TLC} + 7.65 \tag{7}$$

where p is the probability of neglect steering

Under-compensation:

$$\text{logit}(p) = 5.73 \times \text{SP2} + 0.15 \times \text{TLC} - 6.94 \tag{8}$$

where p is the probability of under-compensation

Over-compensation:

$$\text{logit}(p) = 2.09 \times \text{SP3} + 0.25 \times \text{STD} - 4.40 \tag{9}$$

where p is the probability of over-compensation

Notes: The measures are summarized across two seconds before the lane departures.

Table 16. The number and percentage of lane departures caused by the predicted neglect steering (Neglect), under-compensation steering (Under), or over-compensation steering (Over) under different distraction conditions

	Neglect	Under	Neglect +Under	Neglect +Over	Total
Baseline condition	6 (60)	4 (40)	0 (0)	0 (0)	10
Visual distraction	129 (68)	15 (8)	4 (2)	42 (22)	190
Cognitive distraction	8 (40)	9 (45)	3 (15)	0 (0)	20
Combined distraction	41 (67)	10 (16)	3 (5)	7 (12)	61

Notes: "+" means two steering failures occurred simultaneously, and there is not case of "Under+Over". The percentage is in parentheses.

A sequential strategy to detect combined distraction

Chapters III and IV developed algorithms to detect cognitive distraction and visual distraction. This section describes approaches to detect combined visual and cognitive distraction using the data collected in the simulator experiment described above. To detect combined distraction, I proposed a sequential approach, which identifies visual distraction first and then detects cognitive distraction with different algorithms depending on whether visual distraction is detected (Figure 31). This strategy was built upon the rationale that visual distraction dominates the effects of combined distraction and that cognitive distraction may be manifest only in subtle differences (e.g., high blink frequency). Eye movements associated with visual distraction may obscure these subtle differences associated with cognitive distraction.

The sequential approach used three algorithms, each of which identified one type of distraction (Figure 31). In this study the distraction was defined using experimental conditions. For visual distraction, the algorithm ("Ongoing-history-linear"), which used the ongoing glance duration and considered glance history, was used to estimate the distraction level. A logistic regression classified the estimated level into "visual distraction" and "no visual distraction" (Algorithm 1 in Figure 31). Based on the results of visual distraction detection, two algorithms were used to detect cognitive distraction under different conditions. If visual distraction was not detected, the layered algorithm in Chapter III (Algorithm 2 in Figure 31) was used to identify cognitive distraction. Otherwise, the sequential approach used the logistic regression model of blink frequency to identify cognitive distraction that might occur simultaneously with visual distraction (Algorithm 3 in Figure 31). Using blink frequency in Algorithm 3 was based on the experimental result that blink frequency increased during cognitive distraction and combined distraction, but not visual distraction. Nonetheless, this relationship may not be the case for every driver because of the large variance of blink frequency shown in Figure 28a. It may be that cognitive component in combined distraction may not be detectable for some individuals.

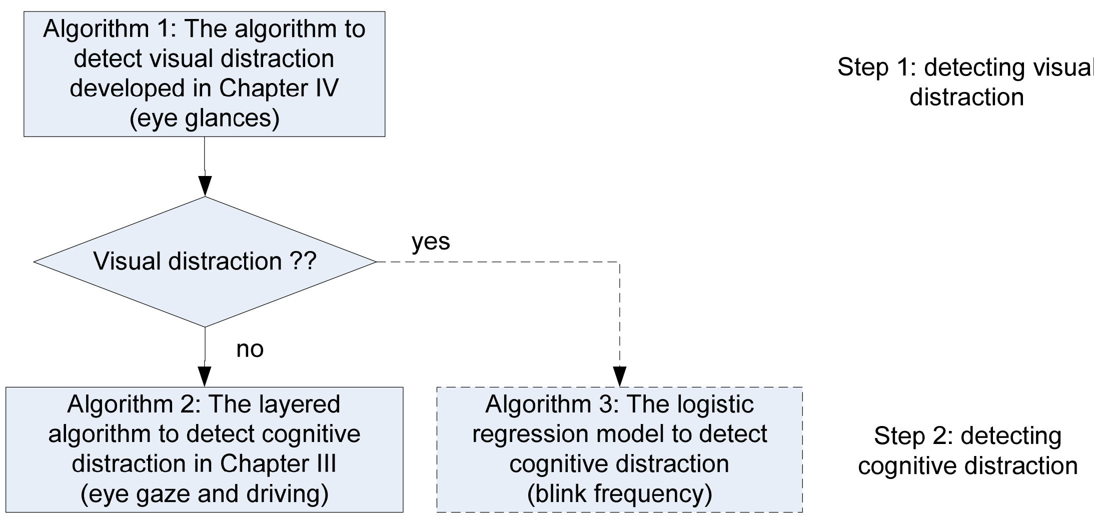


Figure 31. The strategy to detect the combined visual and cognitive distraction.

To train the three algorithms, the experimental data for each condition were randomly divided into two sets: 1/3 and 2/3. The set with 2/3 of all data served as training data, and another proportion served as "unknown" instants to test whether this sequential approach could identify different types of distraction. The testing accuracies and misclassification rates were used to evaluate the performance of this sequential approach. Specific measures included the overall accuracy, the accuracy for identifying each type of distraction, the accuracy of each algorithm, and the rates of classifying visual distraction and combined distraction as the wrong type of distraction.

Table 17. The inputs of detection algorithms

Algorithm	**Input variables**
Algorithm 1 (Ongoing-history-linear)	Instantaneous glance duration
Algorithm 2 (Layered algorithm)	**Eye movement temporal measures** Average blink frequency Mean and standard deviation (SD) of fixation duration, saccade duration, pursuit duration, pursuit distance and pursuit speed Average off-road glance duration, on-road glance duration and off-road glance frequency **Eye movement spatial measures** Mean and SD of horizontal and vertical fixation location coordinates, saccade distance, saccade direction, saccade speed and pursuit direction **Driving performance measures** SD of steering wheel position Mean steering error SD of lane position
Algorithm 3 (logistic regression)	Average blink frequency

Detecting visual distraction ("Ongoing-history-linear")

The "Ongoing-history-linear" uses the ongoing glance duration and glance history as the input (Table 17). This algorithm was chosen to identify visual distraction because it could capture the impairments caused by frequent off-road glances. Even though the analysis of the naturalistic data showed that the glance history did not affect crash risk, it was included here because long interactions were quite rare in the 100-Car dataset, but might become more common as complex secondary tasks requiring multiple off-road glances become more common (e.g., text messaging and selection from an MP3 playlist). These tasks may be associated with future in-vehicle systems and not be included in the 100-Car Study dataset. Therefore, capturing glance history was critical to estimate visual distraction for this experimental dataset.

With the estimated visual distraction, two analyses were conducted. The first analysis was similar to that in Chapter IV of using estimated visual distraction to identify the increased risk of safety mishaps, defined as lane departures in this experiment. This analysis used an odds ratio to identify the relative contribution of different types of secondary tasks to the likelihood of safety mishaps compared with the estimated visual distraction. If off-road glances were the major contribution of lane departure, the secondary tasks were expected to contribute little to the odds ratio for lane departure when the algorithms estimate of visual distraction was already considered in odds ratio. The second analysis used logistic regression to identify when drivers were performing the secondary tasks with visual demands according to the estimated visual distraction by "Ongoing-history-linear". Logistic regression is one of the most basic classification methods and can be easily interpreted. No other complex methods (such as, SVMs) were needed in this simple classification application. This model predicted the experimental condition as a function of visual distraction as estimated from the eye movement behavior.

In the first analysis, the mishap epochs, analogous to the 100-Car dataset, included five seconds before and after lane departures because drivers took some time to adjust the vehicle back to the lane after lane departure. The baseline epochs were also 10 seconds long and exclusively sampled in the data that were not associated with lane departures. The estimated distraction level at the point of lane departure and end of the baseline epochs was used to calculate the odds ratio for lane departure at different distraction levels. As in the analysis of the naturalistic data, the distraction levels were determined using the percentile division. The odds ratio was calculated using a logistic regression (*logit(mishaps)=A+B*distraction_level)*, and a linear regression model was fitted to describe how the odds ratio of lane departure changed with distraction level. Examining this linear relationship, a cutoff level of visual distraction, above which the odds ratios of lane departure for distraction level were greater than one, classified the data into "high visual distraction level (HV)" or "low visual distraction level". To identify the relative contributions of secondary tasks to the risk of lane departure compared with "high visual distraction level", the odds ratios of lane departure calculated from two logistic regression models— (1) *logit(mishaps)=A+B*HV* and (2) *logit(mishap)=A+B1*HV+ B2*experimental_condition+B3*interaction* (*interaction*: the interaction of "high visual distraction level" and experimental conditions)— were compared for each experimental condition. The difference between the two odds ratios indicates the contribution of secondary tasks to crash risk compared with "high visual distraction level".

In the second analysis, the estimated visual distraction was used to predict experiment condition using a logistic regression model (*logit(experiment_condition)=A+B*distraction_level*). The dependent variable of the logistic regression model was the binary variable defined by the baseline and cognitive distraction conditions as "no visual distraction" and visual and combined distraction conditions as "visual distraction". The independent variable was the estimated visual distraction by "Ongoing-history-linear". The model was trained using the training data (the sets with 2/3 of data) from baseline and visual distraction conditions and tested using the testing data (the sets with 1/3 of data) from all experimental conditions.

Detecting cognitive distraction

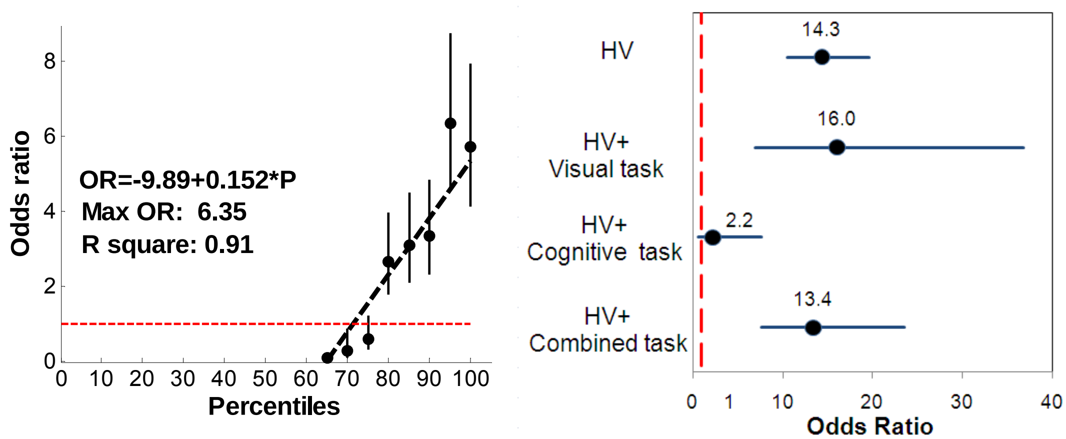
Based on the identification of visual distraction, two algorithms were implemented to detect cognitive distraction. When visual distraction did not occur, the layered algorithm in Chapter III, Algorithm 2, was used to detect cognitive distraction; and when visual distraction did occur, a logistic regression of blink frequency, Algorithm 3, was used to detect cognitive distraction. Using logistic regression for Algorithm3 was with the same reason of using the method in Algorithm 1. Algorithm 2 was trained with the training data from the baseline and cognitive distraction conditions, the inputs of detection algorithm shown in

Table 17 was summarized across 30 seconds, and the parameter settings and training tools were the same as those in CHAPTER III. Algorithm 3 was trained with the data from the baseline and combined distraction condition, the input was average blink frequency across 30 seconds. The same as Algorithm 1, both Algorithm 2 and Algorithm 3 were tested using the testing data from all experimental conditions.

Visual distraction and the risk of the safety mishaps

The odds ratio of lane departures increased with the visual distraction estimated by "Ongoing-history-linear" (Figure 32a). The fitted linear regression model of the odds ratio had a high slope of 0.152 and R-square of 0.91, and the maximal odds ratio was 6.35 (95% confident interval: 4.60~8.76). Because odds ratios started to become greater than one at the 75th percentile (Figure 32a), this point was chosen as the cutoff point to classify high or low visual distraction level for this analysis.

The odds ratio calculation showed that the risk of lane department at "high visual distraction level" was approximately 14 times the risk of "low visual distraction level" (OR: 14.3, CI: 10.5, 19.6; Figure 32b). Interestingly, adding visual distraction condition or combined distraction condition into the logistic regression model did not change the overall odds ratio of lane departure (visual task, OR:16.0, CI: 7.0, 36.8; combined task, OR: 13.4, CI: 7.6, 23.5), while adding cognitive distraction decreased the overall odds ratio to the level that was not significantly greater than one (OR: 2.2, CI: 0.6, 7.6). The similar odds ratios for visual and combined tasks show that the contributions of the secondary tasks to the risk of lane departures are largely associated with driver off-road glances. Therefore, to mitigate distraction the adaptive systems should focus on reducing driver off-road glances.



(a) (b)

Figure 32. The estimation of visual distraction with the risk of the lane departure. The solid dots indicate the value of odds ratio, and the vertical and horizontal bars across the dots indicate the 95% of confident interval of the odds ratio. The dashed line indicates that odds ratio equals to one.

The reduced odds ratio for the cognitive task was caused by the significant interaction between visual distraction level and the involvement in the task. During the cognitive tasks drivers tended to look to the road all along, meaning that the cognitive task diminished off-road glances and produced smaller risk relative to those tasks with visual demands. Because the baseline data used in this analysis contained all four experimental conditions, the odds ratio that was not statistically greater than one does not mean that cognitive tasks did not increase the risk of lane departure relative to attentive driving. At the same time, the selection of the cutoff point can influence the odds ratio. The cutoff point used in this analysis was relatively small compared with the ranges of estimated visual distraction (Figure 33), which implies that some “low visual distraction level" cases might be miss-categorized as HV. These errors can seriously influence the odds ratio for cognitive tasks because the estimated visual distraction under cognitive tasks has a relative small range and the change of the cutoff points can greatly alter the proportion of lane departure under HV and cognitive tasks. Therefore, a large cutoff point for HV may change the odds ratio for cognitive tasks.

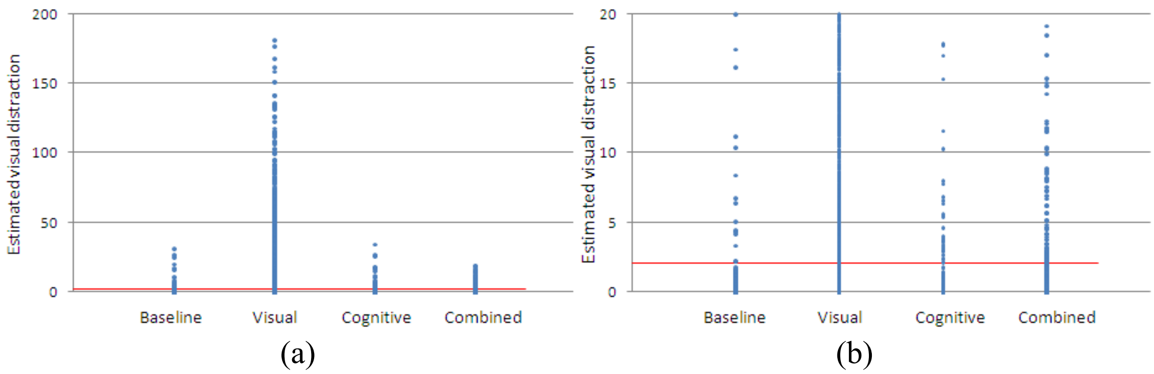


Figure 33. Estimated visual distraction under different experimental conditions. (b) shows a subset of (a) when the estimated visual distraction is in the range from zero to 20. The horizontal lines indicate the cutoff point for high visual distraction.

Detection of combined distraction

The overall accuracy of the sequential approach and the accuracy for visual and combined distraction were low (overall: 57.1%; visual: 45.6%; combined: 5.2%; Table 18). However, these low accuracies might not be only caused by poor algorithms, but also by the inappropriate definition of distractions. The characteristics of the combined secondary task determined that drivers spent much time on listening to the auditory messages, which mainly imposed cognitive demands on drivers. The time when drivers looked away from the road to the interface (visual demands of the secondary task) was actually very limited and might not be captured by the detection algorithms, which sampled driver behavior every 30 seconds. On average, the proportion of time when drivers looked to the interface in the combined distraction condition was about 20%. Consequently, it is not surprising to see that 56.25% cases of combined distraction were misclassified as cognitive distraction and the accuracy of Algorithm 1 was only 69.6% (Table 18). It may be more appropriate to define the combined distraction condition as cognitive distraction than the original definition.

Defining the combined distraction condition as cognitive distraction seems to contradict the conclusion that visual distraction dominates the effects of the combined distraction condition. But, different from the experimental conclusion that describes an overall trend of driver behavior based on the summarized performance measures, the detection of driver distraction, especially visual distraction, focused on driver distraction states at a more refined time scale. The combined tasks imposed cognitive and visual demands in an alternating rather than simultaneous manner, and the effects of the cognitive demands tend to persist for a much longer time than visual demands. It is reasonable to define distraction based on the duration of demands imposed on drivers in distraction detection. Moreover, from the perspective of the proportion of time associated with visual and cognitive demands during the combined tasks, this definition adjustment is not contradictory, but strengthens the conclusion about the domination of visual distraction because visual demands took shorter time, but greatly influence the overall trend of driver distraction.

Table 18. The testing accuracy (%) to evaluate the sequential strategy to detect driver distraction

Distraction definitions		Experimental conditions	Modified definitions
Overall accuracy		57.14	75.04
Accuracy for types of distraction	Baseline(B)	86.41	86.41
	Visual (V)	45.57	77.08
	Cognitive (C)	76.56	66.80
	Combined (Com)	5.21	n/a
Accuracy for algorithms	Algorithm 1	69.55	91.99
	Algorithm 2	65.60	66.00
	Algorithm 3	60.33	n/a
Misclassified rate	Com-to-B	33.59	n/a
	Com-to-V	4.95	n/a
	Com-to-C	56.25	n/a
	V-to-B	6.51	6.51
	V-to-C	16.41	16.41
	V-to-Com	31.51	n/a

With the alternating pattern of visual and cognitive demands, the cognitive demands during the combined tasks tend to dilute the effects of visual demands on driver behavior. This suggests that identifying cognitive distraction is not necessary when drivers are visually distracted because cognitive demands may actually mitigate the effects of visual distraction. Therefore, the sequential strategy can be modified by deleting Algorithm 3 (Figure 34), and the output of the detection is the existence of visual distraction or cognitive distraction. After the adjustment of distraction definition and sequential strategy, the overall accuracy and accuracies of visual distraction and

Algorithm 1 improved (Table 18), demonstrating that the modified sequential strategy of detecting distraction is effective.

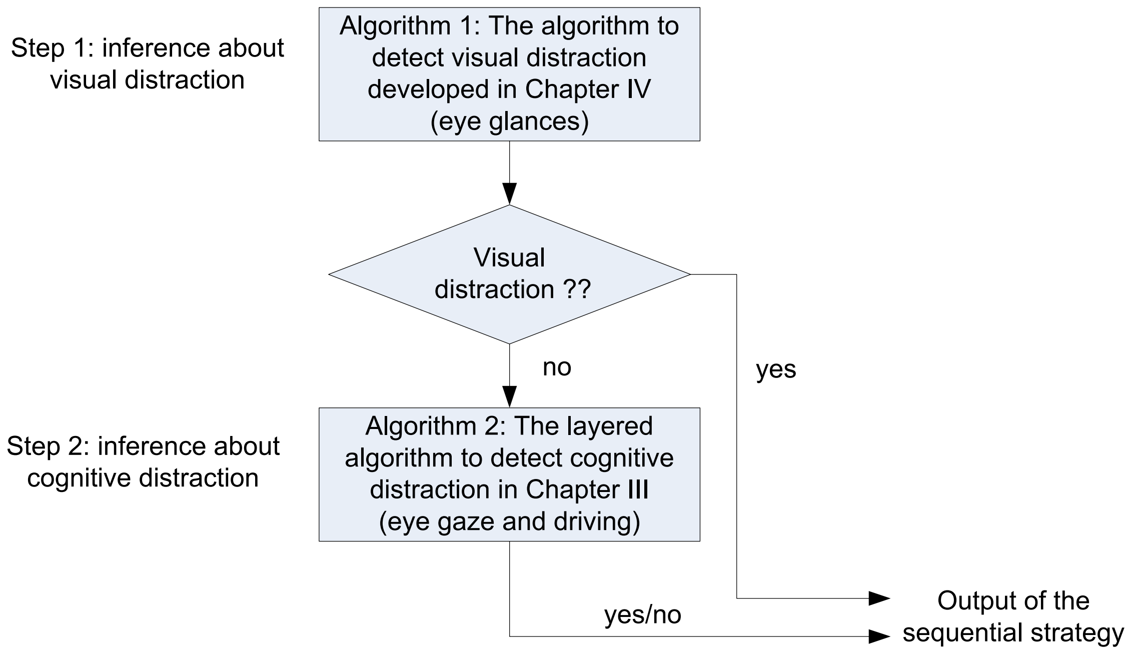


Figure 34. The modified sequential strategy to detect driver distraction.

Discussion

Consistent with the hypothesis, visual tasks interfered with lateral control and hazard detection more than cognitive tasks. Although drivers intermittently looked back to the roadway to maintain safety, the visual task still led to abrupt steering control, large lane variance, and slow response to the LV brake events, which accords with the previous studies (Dingus et al., 1997; Donmez et al., 2007), and is correlated with the increased eye-off-road time.

In contrast, the cognitive task actually reduced off-road glances and improved lane-keeping performance, but made steering more abrupt, which is consistent with Engström et al. (2005). One explanation for the diminished lane variance with the cognitive task is that drivers might realize the increased risk caused by the secondary task and so might adopt a cautious strategy—maintaining a larger safety margin (distance) to the lane boundaries, which is reflected as improved lane maintenance. The more abrupt steering might reflect the combination of maintaining a larger safety margin and degraded control associated with how the cognitive demands impede the processing of roadway information and cause drivers to use an intermittent control strategy (Cliff, 1973). An alternative explanation for the improved lane keeping is that gaze concentration improves tracking response due to enhanced perceptual input (Engström et al., 2005). However, this possibility is not supported by this study because gaze concentration can explain only 5% variance of lane position variation. Most likely gaze concentration and a cautious strategy combine to increase drivers' sensitivity to small changes in heading, leading to more frequent and less smooth steering control and better lane keeping.

Contrary to previous studies (Recarte & Nunes, 2000, 2003), the cognitive task did not have a significant effect on hazard detection. One explanation is that the gaze concentration, salience, and predictability of the LV braking events worked together to enhance drivers' response to the events in this study. Another explanation concerns the processing stage of cognitive demands. The results of some studies show that cognitive load associated with response production (e.g., generating a response during conversation) produces more interference to driving than perceptual load (Levy, Pashler, & Boer, 2006; Recarte & Nunes, 2003). Listening and mental transformation of information represented the majority of cognitive demands in this experiment and may have a relatively mild effect on hazard detection.

The results of this experiment confirm that blink frequency and gaze concentration are promising indicators of cognitive demand. A similar study that only considered cognitive distraction found that blink frequency increased during a secondary task and was the most indicative predictor of cognitive distraction (Liang, Lee et al., 2007). The increased blink frequency and its persistence after the tasks with visual demands may reflect transient fatigue (Cumming & Croft, 1973) caused by these tasks and the demands associated with recovering an awareness of the driving situation after a period of limited sampling. Gaze concentration occurred in all three distraction conditions. Previous studies have primarily focused on gaze concentration associated with cognitive distraction (Recarte & Nunes, 2000, 2003), but on-road eye movement patterns during visual distraction are relatively unexplored. This study found that gaze concentration was not a unique characteristic of cognitive distraction, but also presented with visual and combined distraction (Victor et al., 2005). It also implies that impairments of visual distraction include not only off-road glances, but also ineffective perception at the driving scene when the eyes return to the road (Lee et al., 2007).

Contrary to our expectations, adding a cognitive demand between the visual demands did not degrade performance more than visual task alone. The combined secondary task influenced drivers in a manner similar to the visual secondary task, but to a lesser degree. During the combined task drivers processed the direction information almost continuously and intermittently looked at the in-vehicle interface. The effects of this intermittent visual demand are present in all vehicle lateral control, hazard perception, and eye scanning patterns; and the effects of the cognitive demands can be seen only in blink frequency, and to a limited extent in the types of lane departures. One explanation for these surprising results is that the visual task required a greater degree of eye-off-the-road time associated with searching the display. The strong association between eyes-off-the-road time and lateral control suggests that the multiple resource theory conflicts associated with visual demand dominates the effect of the secondary tasks on lateral control. Combining cognitive demands with visual demands in the sequential way did not produce greater interference than the visual demands. These results are generally consistent with the general finding that visual demands dominate distraction-related declines in driver performance (L. Angell et al., 2006; Carsten et al.,

2005) and distraction-related increased risk of crashes and near crashes (Klauer et al., 2006).

The analyses of the odds ratio for lane departure and the sequential distraction detection strategy both demonstrated that visual demands associated with secondary task is the major impairment of distraction. This finding reinforces the recommendations that the design of in-vehicle systems needs to limit visual demands that are imposed on drivers when they use the system and provide alternative mode of operation that requires none or a little visual demand. For example, auditory systems and voice recognition can replace manual operation to avoid off-road glances of drivers. Because visual distraction seems to dominate, the future research on adaptive distraction mitigation systems should focus more on the mitigation of visual distraction. Accurate estimation of visual distraction may be the most important component of the detection systems for driver distraction.

Generalization from driving simulator studies is limited by the degree to which the simulator presents drivers with roadway demands that are representative of actual driving situations. The situations in this study are only partially representative of actual situations, particularly with respect to the relatively predictable hazards. Many crashes result from rare, unpredictable, and more severe hazards than those in this experiment, and distractions might compromise response to these situations to a greater or lesser extent than what was observed in this experiment. The scenarios used in this study had the advantage of being highly repeatable and producing behavior that could be precisely quantified.

Similarly, the relatively low-fidelity simulation of a navigation system provided precisely controlled cognitive and visual demands that were generally representative of actual systems. Using an actual navigation system would make it impossible to isolate the visual and cognitive demands and quantify their effects on driver performance. However, most participants completed approximately three times as many selections from the display with the visual task compared to the combined task in the same length of period. This difference points to the substantial challenge of simulating secondary tasks and equalizing the demands of tasks that require different types of processing resources. Precisely documenting the demands of secondary tasks and driving task is essential for the simulator studies. For example, the precise demands associated with hand-held or head-free cell phone interactions in simulator studies may differ substantially from the demands associated with those devices in actual driving situations—the visual demand of dialing may dominate the distraction, which is typically neglected in simulator studies. A GOMS analysis is a promising tool to define task demands and set generalization bound for the study of using the tasks precisely. The driving simulator and in-vehicle information system simulator used in this experiment illustrate the need to document the critical balance between representativeness, experimental control, and generalizability when selecting simulated tasks.

Conclusions

In conclusion, visual distraction interferes with driving more than cognitive distraction. When two types of distraction occur in combination, the visual distraction component dominates the effects of the distraction on driver performance. The combined distraction is less detrimental than visual distraction, and the cognitive component can actually dilute the visual demands, reducing the overall impairment on driving performance, when two types of distraction are combined in the sequential way.

Three types of steering failures are the primary causes of lane departures and reflect the effects of different types of distraction: steering neglect and over-compensation with visual distraction and under-compensation with cognitive distraction. The analysis of lane departures shows that visual distraction usually causes more urgent danger than cognitive distraction, especially when the driving circumstance is complex and changing quickly. An odds ratio analysis shows that off-road glances associated with visual distraction are the major impairment of driver distraction, which leads to lane departures.

When both visual and cognitive distractions may occur, the effective approach to detecting them is to identify visual distraction first because it impairs safety more than cognitive distraction and to detect cognitive distraction only when no visual distraction occurs.

CHAPTER VI. GENERAL CONCLUSION

Driver distraction is a leading cause of motor-vehicle crashes. Developing distraction mitigation systems that adjust their functions to reduce the impairment of distraction according to driver state can help to reduce distraction-related crashes. For such a system, accurately recognizing driver distraction is critical. This dissertation contributes to the development of new algorithms to detect driver distraction.

One challenge of detecting driver distraction is to develop the algorithms suitable to identify different types of distraction. Visual distraction and cognitive distraction are two major types of distraction, which can be described as "eye-off-road" and "mind-off-road", respectively. The effects of these types of distraction on driver behavior determine how to develop detection algorithms. Visual distraction disrupts continuous visual perception of the roadway through off-road glances and presents severe, obvious and consistent impairments to driving. This dissertation shows that estimation of visual distraction requires a general algorithm considering instantaneous change of drivers' eye glance activities. In contrast, cognitive distraction interferes with driver information processing and decision making. The effects of cognitive distraction are subtle and inconsistent and have no simple indicators. The detection of cognitive distraction therefore needs to consider a comprehensive view of driver behavior across a relatively long period of time, which requires complex algorithms personalized for different drivers. Moreover, depending on the characteristics of secondary tasks, visual distraction and cognitive distraction can occur in combination. When the two types of distraction occur simultaneously, their effects on driver behavior can be interactive, which requires detection algorithms to adjust accordingly. The research gaps addressed by this dissertation concerning detecting driver distraction include assessing the interaction of visual distraction and cognitive distraction when they occur in combination. Quantitative methods to detect visual, cognitive and combined distraction have not well developed.

This dissertation tested the central hypotheses that 1) when visual and cognitive distraction occurs in combination, the effects of the combined distraction are dominated by visual distraction and with severer impairments because of the co-occurrence of the cognitive distraction, and 2) quantitative methods, especially data mining methods, can be used to construct the models to detect visual, cognitive and combined distraction. To examine these central hypotheses, three specific aims were fulfilled. The first aim developed the layered algorithm that integrated two data mining methods to improve the detection of cognitive distraction. The second aim developed algorithms to estimate visual distraction and demonstrated the strong relationship between visual distraction and crash risk using the naturalistic data. The third aim examined the interaction of visual and cognitive distraction when they occurred in combination and developed an effective strategy to detect the combined distraction.

The first aim demonstrated that the layered algorithm improved the detection of cognitive distraction by significantly reducing computational load and achieving similar prediction performance as the previous approach. This method also provided interesting insights into the effects of cognitive distraction on driver behavior were discovered from the trained detection models. Therefore, data mining methods are a promising approach to identify complex human behavior, especially the behaviors that have not been clearly understood.

The second aim revealed that visual distraction estimated by analyzing drivers' eye glance patterns could indicate crash risk. Three characteristics of eye glance patterns, including glance duration, history and location, were used to describe drivers' eye glance patterns. Visual distraction estimated by the algorithms considering the instantaneous changes of off-road glances was the most indicative of crash risk. Unexpectedly, some variables of eye glance patterns including 1.5th power of glance duration, glance history, and eccentricity of glance location did not improve the algorithms. Different from the first aim (detection of cognitive distraction), this aim was built upon the naturalistic 100-Car Study data, which made it possible to link distraction estimation to the risk of crashes in real driving situations. The difficulty of manipulating cognitive distraction in the naturalistic data makes hard to study the combined distraction with this dataset.

The third aim demonstrated that visual distraction is the major impairment when the two types of distraction occur in combination. In a simulator experiment, visual distraction dominated the effects on driver performance. Contrary to the central hypothesis, combined distraction was less detrimental than visual distraction because cognitive distraction actually dilutes the effects of visual demands by interrupting continuous visual secondary demands. Visual distraction led to more lane departure in the experiment. Three types of steering failures were found as the primary causes of lane departure occurred. Distraction contributed to these failures in different ways: 1) steering neglect and 2) over-compensation with visual distraction and 3) under-compensation with cognitive distraction. Steering neglect and over-compensation were the most frequent types of failure to occur and directly associated with off-road glances. An odds ratio analysis showed that the visual distraction level estimated from driver eye glance patterns could explain most increased risk of lane departure. Therefore, the effective approach to detecting the combined distraction is to detect visual distraction first and then detect cognitive distraction only when visual distraction does not occur.

Merging the findings from all three aims, it can be concluded that visual distraction is the primary impairment associated with secondary tasks and can account for large proportion of the variance in crash risk. This finding reinforces the importance of designing in-vehicle systems to limit visual demands that are imposed on drivers when they use the system and provides alternative mode of operation that requires none or a little visual demand. For example, auditory systems and voice recognition can replace manual operation to avoid off-road glances of drivers. With the dominating impairment of visual distraction, the future research on adaptive distraction mitigation systems should focus more on the mitigation of visual distraction.

Quantitative methods, especially data mining methods, can be used to detect driver distraction. The computational process should be tailored according to the effects of distraction on driver behavior. With obvious and consistent effects, visual distraction can be estimated by a general model that describes the instantaneous changes of drivers' eye glance patterns and fits all drivers. The estimated visual distraction strongly relates to crash risk. In contrast, the effects of cognitive distraction are subtle, inconsistent and cumulative. The detection of cognitive distraction considers a comprehensive view of driver behavior across a relatively long period of time and needs to be personalized for individual driver. Data mining methods are a promising approach to capture such complex relationships. The approaches used for detecting visual and cognitive distraction can be generalized to monitor other types of performance impairment, like driver fatigue.

Extending from this dissertation, a promising direction is to generate a computational model of human cognitive impairments (distraction, fatigue, and aging) in various behavior fields. In research on driving, there are three dimensions to extend this research: impairments (e.g., fatigue and alcohol use), sensor technology (e.g., physiological signals), and algorithms (e.g., Dynamical Bayesian Network). Future research could focus on developing and validating real-time detection systems for distraction and fatigue using indicative behavioral predictors and time-series algorithms. Such approaches could also apply to other domains, including Human Computer Interaction (HCI) and medical practice, both of which suffer from cognitive impairments of human operators/practitioners and people might benefit if the computer system could understand and respond to their state.

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