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16. Abstract

Despite government efforts to regulate distracted driving, distraction-related fatalities and injuries continue to increase. Manufacturers are introducing real-time driver monitoring systems that detect risk from distracted driving and warn drivers; however, little is known about these systems. This report identifies evaluation techniques to characterize and assess these emerging technologies, presents results of their application, develops a framework for estimating systems' safety benefits, and provides safety relevant information to guide technology development. A standardized language for describing and differentiating systems was created, and its application revealed key trends in the design landscape. A novel approach to detection that provides prospective indications of safety-critical vehicle state changes is described. Two evaluation protocols were developed and to provide empirical assessments of (1) detection algorithm performance and (2) the effect of mitigations on driver performance and acceptance. The protocol included driving on different types of roadways and performing secondary tasks in the high-fidelity NADS-1 driving simulator. Four progressively complex distraction detection algorithms were compared to evaluate the ability of vehicle-based systems to distinguish between distracted and non-distracted drivers. Algorithm performance varied across road types and distraction tasks. A safety benefits framework appropriate for distraction mitigation systems is proposed that expands on past benefit analyses.

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Appendix A: Theoretical and Empirical Considerations for Distraction Detection And Mitigation

This appendix describes the mechanisms of distraction and provides a theoretical and empirical basis for distraction detection and mitigation. The mechanisms of distraction are used to review potential sensors for distraction detection. It also outlines strategies for distraction detection and mitigation, as well as the sensor requirements associated with those strategies.

Distraction and Competing Resources

Figure 1 shows the relationship between the demands associated with a competing activity and the roadway demand. Distraction occurs when the combined demand exceeds the driver's capacity. To some degree drivers can manage the roadway demand by, for example, driving more slowly or maintaining a greater headway (Donmez et al., 2008a), although the evidence for such compensatory behavior is mixed (Caird et al., 2008; Horrey & Simons, 2007). Unfortunately, driving demands are not always predictable and are often out of the driver's control—for example, other vehicles may brake abruptly and unexpectedly. Although drivers are able to manage their engagement in competing tasks, they often fail to prioritize driving relative to them and to compensate adequately for their demands (Jamson & Merat, 2005), particularly during tactical maneuvers, such as passing other vehicles (Horrey & Simons, 2007). Furthermore, drivers may not be aware of the performance decrement associated with distracting activities (Horrey et al., 2008) and tend to believe they are able to drive more safely while distracted than the average driver (White et al., 2004). As a consequence drivers may fail to delay or interrupt a competing activity during demanding driving situations.

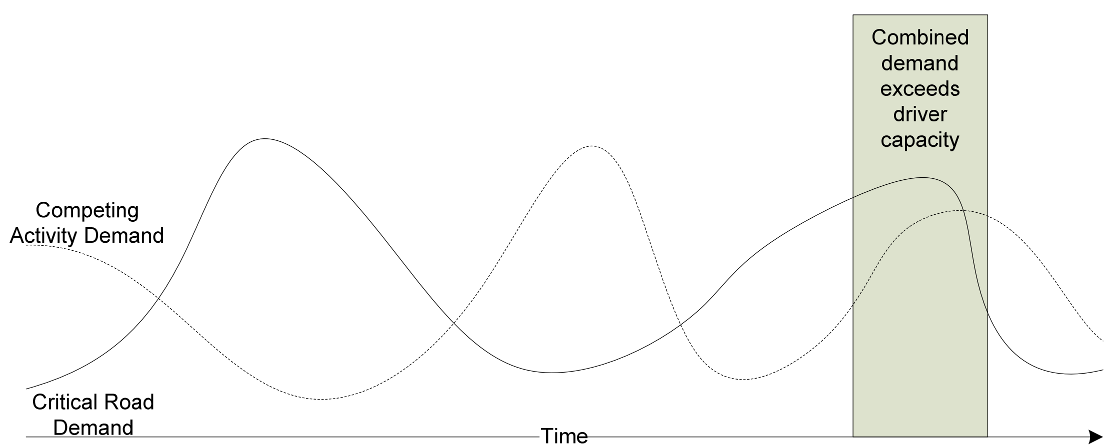

Figure 1 The interaction between roadway demands and competing activities that contribute to distraction-related mishaps (Lee et al., 2008a).

The moment-to-moment description of distraction at the operational level that is shown in Figure 1 can be described in terms of the competition between driving and information processing resources. Removing hands from the wheel or moving the body out of the standard driving position, such as reaching to the passenger seat for a ringing cell phone, leaves the driver less able to respond to demanding driving situations. Likewise, looking away from the road to read a text message, for example, leaves the driver unable to detect roadway events. More subtly, cognitive processing, such as that which occurs while engaged in a hands-free phone conversation, leaves the driver less able to process driving-related information (Lee et al., 2007; Strayer & Johnston, 2001) .

Multiple resource theory (MRT) describes these different types of competition between driving and distracting activities in terms of four dimensions: processing stage (i.e., perception, central processing, and response), processing code (i.e., analogue/spatial or categorical/verbal information), perceptual modalities (i.e., visual or auditory) (Wickens, 2002), and visual channel (i.e., focal or ambient vision) (Horrey & Wickens, 2004). Driving performance declines to the extent that the competing task shares resources with the driving task. This is perhaps most obvious at the perception stage, with competition between visually demanding distractions and the intense visual demands of driving. More subtly, the response selection stage acts as a bottleneck to cognitive operations so that driving and distracting activities must be performed serially. Even though a competing task might have a processing code that would not seem to conflict with driving—such as a conversation—a response selection bottleneck could delay responses to driving events while a response is being prepared for the competing activity (Levy et al., 2006). The different types of resources suggest different metrics are needed to detect distraction and capture the effect on driving safety.

Most distracting activities involve some combination of information processing resources, but three general categories of distraction merit distinction based on their effects on driving safety and the means by which they can be detected: manual (e.g., reaching while still looking at the road), visual (e.g., reading from a display), and cognitive (e.g., thinking and conversing about a non-driving task). Manual, visual, and auditory/cognitive distraction can be described as “hands-off-wheel,” “eyes-off-road,” and “mind-off-road,” respectively.

Any task can have a combination of manual, visual, and cognitive components at different levels. With a visual task, the lowest level requires drivers to take their eyes off of the road, the next level requires them to turn their head, and the highest level requires them to shift their entire body. The lowest level of a manual task requires drivers to take a hand off the wheel. The next level of a manual task requires drivers to move their entire arm, and the highest level requires them to move their body. The cognitive component of a task also has varying levels ranging from no thought to simply listening and comprehending to selecting a response based on incoming and recalled information.

Visual and manual tasks affect driving performance more than cognitive tasks, leading to large and frequent lane deviations, uneven steering control, and slow response to lead vehicle braking (Dingus et al., 1989; Jamson & Merat, 2005). When the driver is looking away from the road, the delay in response to a braking lead vehicle can be as long as the duration of the glance—exceeding several seconds. Cognitive distraction affects driving by disrupting the allocation of visual attention to the driving scene and the processing of attended information (Lee et al., 2007; Strayer & Johnston, 2001). It causes drivers to concentrate their gaze in the center of the driving scene, as defined by the horizontal and vertical standard deviation of gaze distribution, and diminishes their ability to detect targets in the periphery of the driving scene (Recarte & Nunes, 2003; Victor et al., 2005). More generally, the results of two meta analyses show that cognitive distraction associated with auditory e-mail systems, performing math calculations, or holding hands-free cell phone conversations delays driver response to hazards by 130 to 250 ms (Caird et al., 2008; Horrey & Wickens, 2006). Cognitive distraction also impairs both implicit perceptual memory and explicit recognition memory for objects, even when drivers look at the objects (Strayer et al., 2003).

The specific safety consequences of different devices and different types of distraction are uncertain, but initial findings suggest the consequences are greatest for the highest level of visual/manual distraction (e.g., reaching), then for complex visual or manual tasks, and least for cognitive tasks. Data from the 100-car study show that reaching for a moving object had the strongest association, with an odds ratio of 8.82, whereas reading had an odds ratio of 3.38 and talking on a handheld device had an odds ratio of 1.29 (Klauer et al., 2006). The confidence interval of talking includes 1.0, suggesting that conversations might not increase the risk of a crash or near-crash event. Test track data from the CAMP program showed a similar effect. Complex visual/manual tasks, such as tracing a route on a paper maze and entering a destination into a navigation system, resulted in approximately ten times the number of trials with a lane exceedence, compared with conversations about biographical information (Angell et al., 2006).

The CAMP data also showed that visual or manual tasks produce a different profile of impairment than cognitive tasks, with visual or manual tasks interfering with lateral control and cognitive tasks interfering with event detection and longitudinal control. These profiles of impairment suggest that the effect on driving safety depends on how the demands of the tasks conflict with the demands of the driving situation. A cognitively demanding task may pose a greater threat in a driving environment that requires efficient event detection, such as negotiating intersections and urban streets. The consequences of a distracting task depend on the specific demands of the driving situation.

Distraction and the Dynamics of Attention

Figure 1 shows that distraction involves more than just competition for information processing resources between driving and other activities; it also depends on how well drivers can direct attention to the roadway when the situation demands it. Four factors combine to govern how attention is directed: Salience, Effort, Expectancy, and Value (SEEV) (Horrey et al., 2006). Drivers direct their attention toward areas that are highly salient, that require little effort (e.g., small visual angle between information sources), that are expected to contain new information, and that have high value relative to the person's goals (e.g., the road ahead for maintaining lateral control).

Figure 2 integrates the elements of SEEV into a description of visual sampling that describes factors governing the dynamics of distraction and how drivers shift their attention between driving and completing activities. It could be expected that safety is most compromised when two or more of these factors combine. For example, when there is a simultaneous occurrence of eyes off road, poor attention to the road scene, and an unexpected critical event. Likewise, even a dangerously long glance away from the road might not have any consequence if it occurs without a critical event.

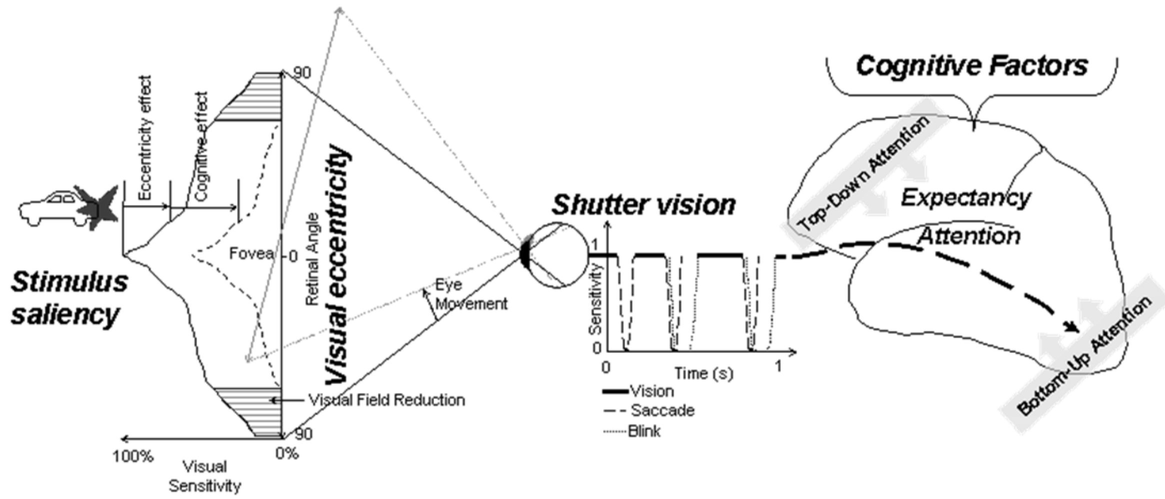

Figure 2 Conceptual framework of key factors influencing the dynamics of distraction in driving (Victor, Engström, & Harbluk, 2009).

According to the conceptual framework of distracted driving presented in Figure 2, the four key factors shaping the dynamics of distraction are:

Stimulus saliency: The ability of a stimulus to capture the driver's attention and generate an appropriate response is highly dependent on stimulus saliency properties such as size, color, contrast, orientation, movement, and luminance (Itti & Baldi, 2005; Rumar, 1990).

Visual eccentricity: The visual eccentricity factor is the effect of stimuli falling on the retinal periphery instead of the fovea (the fovea is the location at which visual processing is centered). A dramatic reduction in the performance of visual functions occurs toward the retinal periphery. For example, a decelerating lead vehicle takes longer to capture the driver's attention the farther the driver is looking from the center of the road (Lamble, Laakso, & Summala, 1999). Visual eccentricity also corresponds to the SEEV dimension of effort in that objects with a higher eccentricity take more effort to attend.

Shutter vision: People do not have access to a continuous stream of visual information. Blinks, saccades, and temporary occlusions result in periods of vision loss that mask visual transient responses of low-level feature detection mechanisms, thus impairing bottom-up attentional capture, event detection, and response (Rensink, 2002). This shutter factor also reflects the intermittent sampling of the roadway that occurs when drivers engage in a competing activity that takes the eyes off the road. Such sampling typically involves glances away from the road that are shorter than 1.5 seconds (Wierwille, 1993), but these glances can be much longer for highly engaging competing tasks and for novice drivers (Wikman et al., 1998). Long glances pose a particular threat to driving safety (Wierwille & Tijerina, 1998). The normally useful illusion of continuous visual information can mask the loss of information during long glances away from the road.

Cognitive factors: Two basic mechanisms guide attention. At one extreme, attention can be dominated by external events in a bottom-up, stimulus-driven manner (Corbetta &

Shulman, 2002). Salience and eccentricity mainly relate to this bottom-up attentional process. At the other extreme, attention can be top-down and goal-directed by cognitive factors such as knowledge, expectation, and current goals. However, attention is most often a combination of these bottom-up and top-down processes, which can be expressed as the product of competitive interactions. Advances in cognitive neuroscience have offered a detailed account of the neural basis for these competitive mechanisms, known as the biased competition hypothesis (Desimone, 1998). The biased competition hypothesis is based on the idea that multiple, hierarchically organized populations of neurons engage in competitive interactions which may be biased in favor of specific neurons by means of bottom-up activation and/or top-down signals originating from outside the perceptual system (mainly from pre-frontal brain areas). This concept accounts for how a cognitively demanding secondary task contributes to distraction by interfering with top-down guidance of attention and impairs the ability to detect task-relevant information.

Although many cognitive factors, such as motivation, influence top-down attention, expectancy is perhaps the most powerful (Corbetta & Shulman, 2002). To expect is to anticipate or consider probable the occurrence of an event and is related to a driver's readiness to respond. Expectancy is a crucial factor influencing response times, errors, and traffic efficiency (Alexander & Lunenfeld, 1990; Evans, 2004). For example, a review of brake response time studies showed that response times increased with the level of expectation associated with the event: 0.75s for expected events, 1.25s for unexpected events, and 1.5s for surprise events (Green, 2000).

Expectations can be seen as projections of experience from different levels of the driving task. At the higher—strategic and tactical —decision-making levels of the driving task expectancies are based on past occurrences (e.g., that vehicles will not respect certain traffic rules), or set by traffic signs regarding upcoming hazards on the roads (Alexander & Lunenfeld, 1990; Evans, 2004). At the operational level, expectation is so embedded in the cognitive process that it alters our perceptions (Mack et al., 1992). For example, drivers compensate for sensory lags caused by biological feedback delays by directing actions to extrapolated future states of the world, such as the future paths of objects (von Hofsten, 1995). Specifically, drivers often steer according to the roadway ahead rather than their current position on the road. Past experiences also affect expectancy, as well as the value or importance that drivers associate with scanning certain areas of the road. Expert drivers tend to focus on areas of the roadway that correspond to likely hazards, while novice drivers tend to neglect these areas (Fisher et al., 2006; Pradhan et al., 2005).

The top-down cognitive and bottom-up stimulus-driven factors highlighted in Figure 2 generally correspond to the elements of SEEV. Salience and effort (i.e., eccentricity) correspond to bottom-up factors, whereas expectancy and value correspond to top-down factors.

Implications for Distraction Detection Algorithms

To be usable by real-time distraction algorithms, these key factors (stimulus saliency, visual eccentricity, shutter vision, and cognitive factors) associated with distraction need to be operationalized into measurable indicators of distraction (sensor signals). Although established distraction indicators will be discussed in greater detail, what follows are general implications of the underlying mechanisms of distraction for its detection and mitigation.

Objective measurement of the *stimulus saliency* is currently a new, but active, research field. Applicable tools may be found in the research by Itti and colleagues (Itti & Baldi, 2005; Itti & Koch, 2001), as well as at www.saliencytoolbox.net. Real-time algorithms of saliency could be applied to video, radar, and LIDAR data in automotive settings. *Visual eccentricity* and *shutter vision* are likely to be measured by automotive-grade eye-tracking sensors of the near future. Although most current gaze metrics tend to be binary, as for example on- or off-road glances, as sensors improve, eye-tracker data can also quantify the eccentricity of gaze—the visual angle away from the road-ahead. *Cognitive factors*, such as top-down attention and expectancy, are more difficult to measure. Nevertheless, indirect measurement is possible by monitoring the functions of the in-vehicle information system a driver has activated. Models of the influence of top-down attention are currently being developed and may be of some use in real-time algorithms (Salvucci et al., 2001). No known quantifications of the degree of expectancy of events are known, except for an initial model (Horrey & Wickens, 2006).

This description of the mechanisms underlying distraction has several important implications for detecting and mitigating distraction:

- Distraction occurs when the demands of driving and a competing task combine to exceed the driver’s capacity to respond. Therefore, driving demands need to be considered, possibly through GPS-based estimates of roadway demand, as well as sensors to estimate traffic density and weather conditions.
- Drivers are active participants in engaging and negotiating the demands of driving and competing tasks, but they tend to underestimate their vulnerability to distraction. Hence, mitigations that moderate drivers’ willingness to engage in distracting tasks could have a considerable safety benefit.
- Each task can have visual, manual, and cognitive components that represent qualitatively different types of distraction posing different threats to safety and requiring different measures to detect. The large effect on crash risk makes detecting distractions associated with reaching and looking particularly important.
- Competition for limited processing resources at the operational level is a dominant description of distraction, but considering distraction at the tactical and strategic levels could lead to mitigation strategies that might otherwise be neglected.
- The factors governing the dynamics of attention (in Figure 2) influence how drivers shift their attention between driving and competing activities, and how competing activities might interrupt attention to driving.

Measures of Driver Distraction and Sensor Technology Tradeoffs

Substantial research has been devoted to detecting driver distraction, such as the SAVE-IT and AIDE projects, and to other real-time driver state detection systems, including those that estimate drowsiness with metrics such as PERCLOS (Bergasa et al., 2006; Dingus et al., 1987). Beyond driving, the concept of augmented cognition has led to substantial developments in measuring operators' mental and physical state to enhance performance. Two recent books provide comprehensive and useful overviews of these research areas: *Driver Distraction: Theory, Effects, and Mitigation (2008)* and *Augmented Cognition: A Practitioner's Guide (2008).* These resources provide a foundation for identifying sensor technology to detect driver distraction.

The tradeoff between sensor technology and measures of driver distraction is mediated by exposure to and the severity of risk associated with different forms of distraction. The exact benefit associated with detecting each type of distraction – cognitive, visual, and manual – depends on the frequency and severity of each type of distraction. The potential benefit may be greatest for visual and manual distractions because they pose the most severe threat to driving safety, and the benefit may be least for cognitive distraction. If the exposure to cognitive distraction is much greater than to visual and manual distractions, then the benefits might favor a focus on cognitive distractions.

The technology tradeoff also depends on the costs of the sensor suite. Cognitive distraction involves a qualitatively different behavioral signature, compared to visual and manual distraction, which is subtler and requires more sophisticated sensors, such as an eye-tracking system. The sensor characteristics taken into consideration include: precision (ability to detect distraction when it occurs), robustness (insensitive to environmental noise), timeliness (indicates distraction without delay), intrusiveness (does not require overt responses or sensors attached to the driver), and cost (would the cost of the system be feasible for inclusion in a production vehicle). The high risk of crashes associated with visual and manual tasks, reaching in particular, suggests that these might offer promising opportunities for detecting and mitigating distraction because sensor technology to detect these distractions might be reliable and inexpensive compared to technology required to detect cognitive distraction.

To examine these tradeoffs, we start the discussion of potential sensors of distraction with driver control inputs and then describe output measures associated with vehicle state and driving performance. The review then considers indicators of distraction based on head and eye movement, as well as physiological measures of driver state. The review concludes with a discussion of how these variables might be integrated, and of several sensors that have no basis in the literature, but emerge as promising based on the theoretical considerations associated with the underlying mechanisms governing distraction.

Driver Control Inputs

Drivers influence and respond to the roadway situation by modulating the steering wheel, brake, and accelerator. These variables represent the response of the driver to changes in the roadway that are not filtered through vehicle dynamics such as speed and lane position. Steering, for example, is an important metric of driver response. It has a relatively short time constant that demands driver input on the order of milliseconds and thus has the potential of providing a very timely indicator of distraction. A wide range of steering wheel measures have been used: standard deviation of steering wheel angle, steering wheel reversal rate, steering wheel action rate, steering wheel entropy, and the high frequency component of steering wheel movement. Visual, manual, and cognitive distractions affect steering wheel movements, but in different ways. A visual secondary task leads to increased steering wheel movements over a wide range of amplitudes (i.e., 2-6 degrees) and frequencies, whereas cognitive tasks cause corrective movements with small amplitudes (less than 1 degree) (Engstrom et al., 2005; Östlund et al., 2006). Extreme manual distractions, such as reaching, might have a direct effect on steering wheel position as the driver's body rotates.

More integrative approaches to understanding steering behavior consider the profile of steering behavior over time. One such approach measures steering entropy, which is the unpredictability in the flow of steering adjustments. Steering entropy is thought to indicate drivers' ability to maintain subjectively chosen safety margins with the expectation that distraction undermines this ability (Nakayama et al., 1999). When the vehicle drifts too far from the intended path, drivers tend to respond with abrupt steering corrections. The steering entropy calculation is based on the mismatch between the predicted steering wheel position associated with a smooth response and the abrupt recovery to a safety boundary incursion. Involvement in a secondary task increases entropy (Reyes & Lee, 2008). Prediction errors and the associated entropy have been shown to be sensitive to both visual and cognitive distraction.

Steering and accelerator inputs are often considered as continuous variables in response to ongoing lateral and longitudinal control of the vehicle. These inputs can also describe drivers' discrete responses to objects and events, which represent another important aspect of driving performance. Event detection and response time measures include number of missed/detected events and brake reaction time. Event detection metrics have shown sensitivity to both visual and cognitive distraction. Victor et al. (2005) include a review of metrics employing naturally occurring objects and events. Response time to a lead vehicle deceleration or braking, with its clear relevance to rear-end crashes, is one of the most commonly used events in distraction studies (Greenberg et al., 2003; Lamble et al., 1999). Other types of events include pedestrian crossings and vehicle pull outs requiring evasive maneuvers (Chisholm et al., 2007). Objects in the driving scene, such as traffic lights and signs, may also require a driver's response. Several studies of distraction have shown poorer reaction times and more missed detections (Strayer & Johnston, 2001). The peripheral detection task is an artificial and controlled version of this phenomenon that shows good sensitivity to cognitive distraction (Jahn et al., 2005; Patten et al., 2004).

A key problem with response time metrics is that they are imperfect indicators of distraction: the peripheral detection task is very intrusive because it requires that drivers perform a task that they would not normally perform, such as pushing a button on a steering wheel once a bicyclist is detected. In addition, for naturally occurring events, it is difficult to determine the starting point or even that an event occurred. Response time metrics would require not just sensors of driver input, but also of the driving context. These sensors might include radar-based indicators of the surrounding vehicles and GPS/map-based indicators of the roadway environment. In contrast, simple metrics of continuous control, based on steering wheel and pedal movement, are easily acquired with sensors that are likely to be a standard part of any future vehicle. However, some vehicle systems, such as adaptive cruise control, automate much of the brake and accelerator pedal modulation, reducing the availability of these as indicators of distraction. If automation removes the driver from direct control of the vehicle, then driver inputs will no longer be available as indicators of distraction.

Vehicle State and Driving Performance

Driver control inputs combine with the driving context, such as the behavior of surrounding vehicles, to influence the vehicle state and driving performance metrics. This review mainly focuses on metrics that quantify performance at the tactical and operational levels of the driving task (Michon, 1985), and only on metrics most suitable for real-time distraction algorithms. The purpose of collecting performance measures is to assess the capability of the driver to perform the driving task within safety margins (Gibson & Crooks, 1938). The focus on performing within "safety margins" reflects the fact that there is no "ideal" driving response or trajectory through a given situation. Instead, driving is a satisfying activity where drivers choose from one of many acceptable trajectories that lie within the safety boundaries—drivers do not generally attempt to stay in the precise center of the road but settle for staying satisfactorily close to the center of the road (Goodrich et al., 2000).

The most common driving performance metrics to evaluate distraction are reviewed in the European Adaptive Integrated Driver-vehicle Interface (AIDE) project (Johansson et al., 2004). Two of the four main categories of metrics reflect vehicle state: longitudinal control (speed and vehicle following) and lateral control (lane keeping, heading angle, time to line-crossing).

The most common types of longitudinal control metrics are speed and headway. The headway metrics can be divided into distance based (e.g., distance headway) and time-based (e.g., time headway and time to collision). Most of the longitudinal control metrics are computed from summary statistics such as the mean, standard deviation, percentile, maximum, and minimum. Importantly, some metrics can be considered at the tactical or operational level. Reduced speed and increased headway can be interpreted as compensation for increased attentional demand (Horrey & Simons, 2007). It is not entirely clear how these compensatory effects should be interpreted in terms of safety. Although such compensation might help the driver manage the increased load, a speed reduction may lead to traffic conflicts with following vehicles. Alternatively, failures of speed maintenance may also reflect the interference of the secondary task at the operational level and may signal degraded capacity to control the vehicle.

Speed measures such as mean speed or speed variability can be used to evaluate distraction. In one study, visual distraction led to decreased speed, whereas cognitive distraction did not influence speed significantly (Östlund et al., 2006). Speed reductions were found in numerous studies with hands-free and handheld cell phones. Time and distance-based headway have also been used to evaluate the effect of distraction. Similar to speed, distance-based headway increased under visual distraction and was relatively unchanged with cognitive distraction. In naturalistic settings, speed can be measured more easily and reliably because it does not depend on radar sensors or face the challenge of identifying the lead vehicle and its speed.

Lateral position is usually defined as the vehicle location on the road relative to the center of the traveling lane. Lateral control measured by the standard deviation of lane position is a very common indicator of distraction and is reported by most driver distraction experiments. As with longitudinal control, lateral control metrics are either distance-based (e.g., standard deviation of lane position) or time-based (time to line crossing), and are computed from summary statistics. Diminished lateral control performance has been demonstrated to correlate strongly with visual in-vehicle information system (IVIS) load (Angell et al., 2006). Although time-to-line-crossing (TLC) metrics are attractive, the distance-based metrics (e.g. standard deviation of lane position and lane exceedance) are simpler, more practical, and generate similar results.

Importantly, cognitive and visual distraction result in different effects on lane keeping performance: cognitive tasks tend to reduce lane position variance whereas visual tasks tend to increase variance (Östlund et al., 2005). Others (Brookhuis et al., 1991; Liang & Lee, in press) have noted a similar "improvement" in lane keeping performance with cognitive load. This may be due to increased gaze concentration towards the road center that is often associated with cognitive distraction. This gaze concentration may make drivers more sensitive to heading and position errors. Alternatively, the improved lane keeping may reflect a tactical adaptation in which drivers maintain more precise lane position because they realize the cognitive load makes them less able to respond to unanticipated events.

As with driver steering and brake control, vehicle state measures of driver response to events can also indicate distraction. Naturalistic driving studies and field operational tests have developed methodologies of near-crash event detection that may be useful for distraction algorithms (Dingus et al., 2006; McGehee et al., 2007). Typically, threshold values on various metrics (e.g., longitudinal acceleration >0. 6g) are applied to identify instances where crash-relevant events may have occurred. Metrics used in these studies include lateral acceleration, longitudinal deceleration, forward time-to-collision, following interval, anti-lock braking system (ABS) activation, yaw rate, and steering angle rate. Although there is not a lot of literature on this metric, jerk (the derivative of acceleration) has also been included as a promising threshold metric (e.g., 10 m/s^3) by several traffic conflict technique researchers (Peltola & Attila, 2007; Nygård, 1999). One common difficulty with the use of these event-based metrics is that noise in the data generates many false positives. At the same time, while difficult to measure, these metrics provide some benefits over the alternatives.

Generally, vehicle state metrics are less easy to measure than driver control metrics because they require additional sensors (radar and camera systems) that are more expensive and produce noisier signals. However, as systems such as adaptive cruise control (ACC) and steering assist systems become more common, the sensors for vehicle state and driving performance metrics may be available at no additional cost. There is a tradeoff; such systems may change the task of driving, making driver performance invisible to these sensors. ACC, for example, automates speed and headway control; therefore, speed would not be a useful indicator of driver distraction when ACC is engaged. Another difficulty with vehicle performance metrics, particularly the near-crash event detection, is that they represent lagging indicators of distraction and might not provide a timely detection of distraction for some mitigation strategies.

Head and Eye Movement

Eye movement metrics are considered the most sensitive metrics for measuring distraction and workload (Angell et al., 2006). Attention and eye movements are strongly linked, and visual behavior is indicative of attention selection related to both the driving and secondary tasks (Findlay & Gilchrist, 2003). Consequently, eye movement metrics are highly sensitive (discriminative, repeatable and valid) to the demands of visual and cognitive non-driving as well as driving tasks (Angell et al., 2006; Carsten et al., 2005; Wierwille & Tijerina, 1998). These metrics can provide a direct indicator of visual distraction and an indirect indicator of cognitive distraction.

Visual behavior has been quantified by a large number of metrics ranging from (a) detailed eye-control metrics – within-fixation metrics (tremor, drift), saccade profiles, smooth pursuit control, and eyelid closure behavior, to (b) medium-detail eye movement metrics – glance behavior and distributions, area-of-interest, transition behavior, and semantically-classified fixations (e.g., pedestrian, sign, tree), and to (c) coarse visual behavior metrics – head movement behavior (position, rotation), and facial direction (on/off road). Detailed eye control metrics can quantify vision interruption (shutter vision) in terms of saccades (fast eye movements) or eye closures (blinks). Saccades and eye closures should be treated as periods with no visual input. Note that coarse descriptions of visual behavior also provide coarse descriptions of distractions. The precision of a metric affects how well it discriminates among types of distraction and how quickly it detects their occurrence. Some of the most promising visual behavioral characteristics and their metrics are defined below.

Pupil dilation and blink rate have been considered reliable measures of mental workload (Recarte et al., 2008; Takahashi et al., 2000). Several recent studies showed that blink rate increased when drivers performed a cognitively demanding secondary task (Liang et al., 2007a, 2007b). In addition to indicating drivers' information sampling, the eyes also provide a window into drivers' physiological response. However, eye-tracking systems that are used in current production vehicles do not have sufficient precision to estimate pupil size. In contrast, eye blink frequency represents a relatively feasible, non-intrusive measure that has been demonstrated to be sensitive to cognitive demand.

Eye glance metrics such as total and single glance duration, glance frequency, and mean glance duration are the most frequent characteristics that were reported in studies of driver distraction. Perhaps the most direct indicator of visual distraction is the visual timesharing revealed in the eye movements. Visual time sharing refers to the pattern of glancing back and forth between the road and an object (e.g., a cell phone) during a visual task (e.g., dialing). Visual time sharing occurs because foveal vision is required by both the vehicle control tasks (event detection, path control, and headway control) and by other tasks such as dialing a cell phone. Visual time sharing metrics mainly quantify the amount of time spent looking on or off the road (at the object of interest), for each glance or for a period of time such as a task interval or an artificial time-window. It was shown that the distribution of single glance duration follows lognormal distribution with a mean between 0.6 and 1.6 seconds (Green, 2002). Total eye-off-road glance duration greater than two seconds in a six-second window increased crash/near-crash risk twofold, relative to baseline driving (Klauer et al., 2006).

In general, the most sensitive visual task metrics implicitly combine glance duration and frequency – Percent Road Centre (PRC) or Total Glance Duration. However, Glance Frequency and Percent Single Glance Durations > 2 Seconds (not mean glance duration) are also highly sensitive metrics. Gaze concentration measures, such as PRC, could be considered a reliable and robust eye movement metric sensitive to both cognitive and visual distractions (Victor et al., 2005). Gaze concentration refers to a reduction in the distribution of scanning behavior resulting in a concentration of gaze towards the road center. Cognitively demanding tasks can cause a driver's gaze to become concentrated at the road center, a tendency that is associated with, but not necessarily directly causally linked to, impaired detection performance. In addition, tasks that cause visual time sharing (e.g., dialing a number) lead to glances back to the road that are highly concentrated to the road center. An investigation of gaze concentration metric sensitivity found that standard deviation of radial gaze angle (the vector sum of the pitch and yaw gaze vectors) is a highly sensitive gaze concentration metric (Victor et al., 2005).

Visual eccentricity refers to the continuous reduction in visual sensitivity that occurs as an image is presented farther away from the fovea. The farther away from road center a driver looks the poorer the information available for event detection and lane keeping. Visual eccentricity is measured as the angle (or distance) away from the road center. Eccentricity can be measured by pitch and yaw or by a vector sum of these. Figure 3 shows how time to collision was affected by the degree of eccentricity of off-road glances to ten positions of an LED display (Lamble et al., 1999). Glance duration away from the road weighted by a penalty function that is defined by the degree of eccentricity may provide a more precise indicator of distraction.

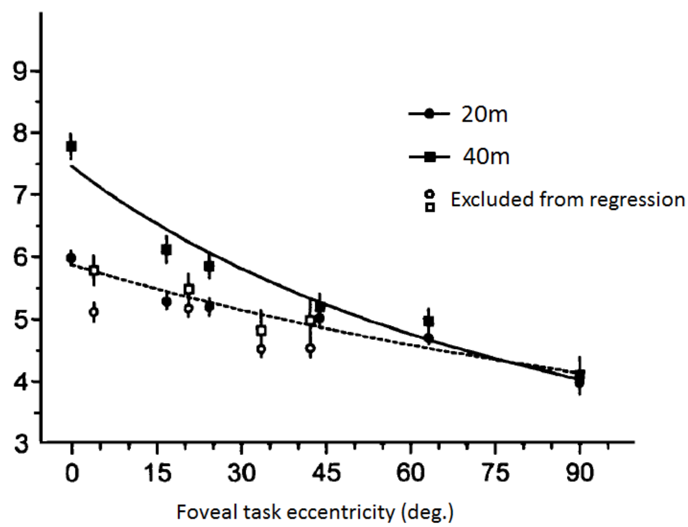

Figure 3 Mean time-to-collision at the point of brake application (in seconds)as a function of foveal task eccentricity for 20 m and 40 m headways (Lamble et al., 1999).

A recent development of a visual demand methodology (Engström & Mårdh, 2007) is a single visual demand metric that accounts for: (1) the duration of each individual glance towards the secondary task, (2) the total number of glances away from the road during the task, and (3) the eccentricity of the glances away from the road. The weighting of the single glance duration uses an exponent to determine the degree to which long glances contribute to crash risk relative to short glances, an idea first proposed by Wierwille and Tijerina (1998). The eccentricity penalty function may be derived from empirical data relating visual eccentricity to detection performance (Engström & Mårdh, 2007). The SafeTE visual demand metric thus explicitly considers glance eccentricity and the effect of long glances.

The outcome of a similar algorithm for estimating visual distraction is shown in Figure 4. The upper curve represents distraction level and it increases when the lower curve is at 1 (indicating glance location) and when the curve stays at 1 longer (indication glance duration). Here, visual distraction is estimated with an exponent of 1.5 for instantaneous long off-road glances and it decreases with on-road glances. The lower curve shows the glance type coded as "1" for off-road and "0" for on-road glances. The upper curve shows how both glance location and duration combined to indicate a much higher level of distraction than might be indicated by glance location alone.

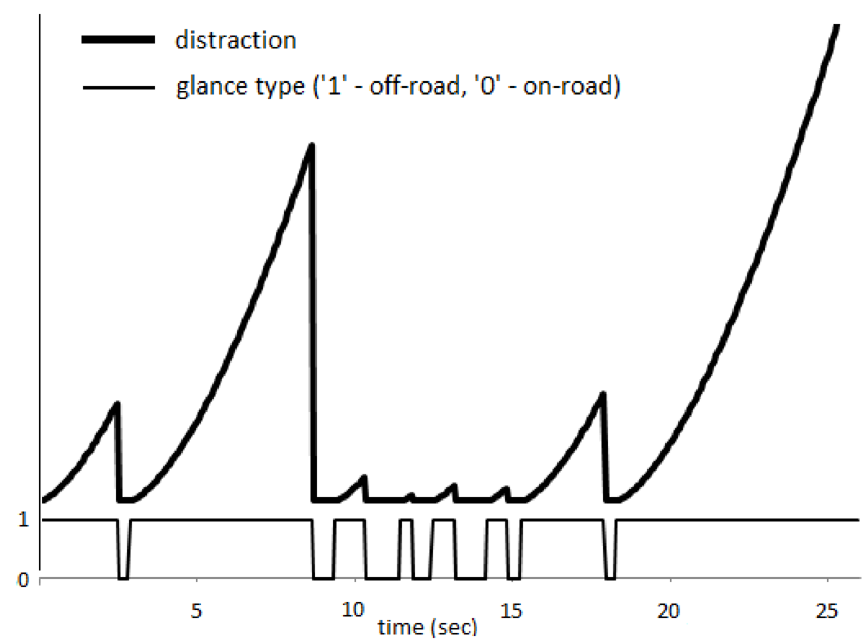

Figure 4 Visual distraction changes with eye glances away from the road.

Further behavioral components that have yet to be explicitly combined into a visual distraction metric are: the duration of glances back to the road, gaze concentration of on-road glances, and visual interruptions. Also, current algorithms do not include action opportunities, such as gaps in traffic or an analysis of the temporal relationships between steering wheel metrics and eye movements. Development of integrated metrics that express the temporal relationships between stimulus-onset and shutter vision (saccades, blinks) would be helpful in explaining missed warning signs that precede a critical event and long response times. Such measures could also incorporate visual eccentricity and the salience (e.g., automatic real-time bottom-up analysis of visual field saliency) of roadway and in-vehicle stimuli. Computational models of eye movement behavior in relation to higher-level goals, top-down attention, expectation, and driving performance may offer a promising approach to creating sensitive indicators of both visual and cognitive distraction (Horrey et al., 2006; Itti & Koch, 2001).

Generally, eye and head movement metrics provide a very promising basis for detecting distraction. Gross measures of head and eye position that can indicate whether the driver is looking at the road are currently implemented in some production vehicles. More precise indicators of eye movements may be possible with emerging eye-tracking technology. Relatively unexplored opportunities for more precise indicators involve combining eye movements with other sensors that characterize the drivers control input (e.g., steering wheel movements) and the driving environment (e.g., GPS and radar).

Physiological Indicators of Driver State

The body exhibits a number of physiological signatures that give a glimpse of the cognitive state of the person. Physiological measures of mental effort include cardiac rate (heart rate and electrocardiography – ECG), electrodermal characteristics (galvanic skin response – GSR), brain activity (electroencephalography – EEG), and eye activity (eye blinks and pupil size). These physiological signals provide continuous information that could be related to changes in cognitive demands. Workload measurement and operator functional state assessment through physiological signals have been pursued in many studies over the last 30 years (Al-Shihabi & Mourant, 2003; Veltman & Gaillard, 1998; Wierwille, 1979; Wilson & Russell, 2003). The overall results have shown that it is very hard to find a unique measure that can be directly interpreted as an absolute indicator of mental effort, but some specific sets of physiological metrics can be good indicators of changes in effort. Identifying distraction is an even greater challenge. Critical issues concerning physiological measures are their cost and the degree to which they can be made unobtrusive so that the sensors do not interfere with normal driving.

As an example, a set of physiological indicators such as electrocardiogram, electromyogram, skin conductance, and respiration were used to evaluate stress level during rest compared with driving in city and highway conditions (Healey & Picard, 2005). Heart rate and skin conductivity metrics detected three levels of driver stress with an accuracy of 97.4 percent. Similar technology has measured stress and fatigue from skin temperature. The results indicated a decrease in nose skin temperature and forehead temperature stability under stressful conditions (Genno et al. 1997). In another study, heart rate and skin conductance along with driver performance metrics were obtained in real and simulated environments while drivers performed visual and cognitive tasks (Östlund et al., 2006). Skin conductance measures were sensitive to changes in task demand in both environments. In real-world driving, heart rate changed significantly while performing the visual task relative to a baseline condition. The difference in heart rate effects between field and simulator driving suggests that visual task performance in real driving was more stressful. This study identified both heart rate and heart rate variability as promising indicators of the driver’s stress level. Heart rate increases and heart rate variability decreases with increases in mental workload. Heart rate variability with an amplitude of 0.1 Hz (mid-frequency band) has been found to be the most sensitive to increased working memory load (Aasman et al., 1987). Cardiac data also have been used to estimate cognitive demand on the driver. Comparing a driving-only condition with driving while performing a secondary working memory task with two levels of complexity showed significantly different responses in heart period or heart rate (Lenneman et al., 2005). Cardiac measures have been found more sensitive to task difficulty than lane position (Lenneman & Backs, 2009).

Studies of neurophysiology that use the EEG to infer mental state have shown that it is possible to infer cognitive activity during different tasks with a good signal-to-noise ratio (Schmorrow & Stanley, 2008). EEG signals can identify specific types of brain activity. For instance, increased alpha activity (8-12 Hz) was associated with decreased mental effort, whereas activity in frontal locations (Theta rhythm: 4-6 Hz) and in the occipital area (Beta activity: 13-30 Hz) indicate an engagement in a cognitive task. As an example, integrated hardware and software called a B-Alert system was developed to analyze the speed of eye blinks and EEG signals from alpha, beta, and theta bands to classify "high vigilance," "low vigilance," "relaxed wakefulness," and "sleepy" operator states (Berka et al., 2004). Head and eye measures coupled with EEG were used to predict low vigilance and lapses of attention (St. John et al., 2004). However, the low spatial resolution of EEG may limit its usage for complex classifications, such as differentiating between various combination of visual and cognitive distraction that might have important implications for crash risk. (Schmorrow & Stanley, 2008).

Although the recent research concerning augmented cognition has shown that physiological measures have become more affordable, more diagnostic, and less invasive, they have yet to provide a feasible tool for production vehicles. EEG and ECG systems remain cost prohibitive and still require electrodes attached to drivers, which would be unacceptable. Even the least intrusive systems require drivers to wear a device on the head or keep their hands free of gloves and on the steering wheel. Other non-ocular physiological measures, such as GSR, require less expensive and less intrusive technology, and therefore may be feasible alternatives.

Summary of Distraction Indicators

Table 4, located at the end of this Appendix, includes a comprehensive list that summarizes potential metrics. Table 1 shows the most promising metrics for detecting driver distraction. The effect size provides a rough estimate, based on the authors' review of the literature regarding the sensitivity of the metric to the difference between distracted and non-distracted driving. The larger the effect size, the more sensitive the measure. Here and throughout the report, rough estimates are shown as filled and open circles. Useful metrics should have high sensitivity to visual, manual, and cognitive distraction and should distinguish among them. The best algorithm will contain the most sensitive metrics that are also uncorrelated. In this way, each will distinguish different aspects of distracted driving from attentive driving.

Table 1 Summary of promising metrics for distraction detection.

Category	**General indicator**	**Specific Indicator**	**Effect size**	**Comments**
Driver control input	Steering wheel	SD of Steering Wheel Angle	○	Very simple and intuitive but not sensitive to cognitive distraction (P. E. Green et al., 2008; Zylstra, Tsimhoni, Green, & Mayer, 2004).
		Steering Wheel Reversal Rate	●	This metric is intuitive and simple but could be sensitive to confounding by environmental and age factors (Green et al., 2008; Östlund et al., 2004).
		Steering entropy	●	Steering entropy is sensitive to distraction and correlates highly with glance metrics (Boer, 2000; Nakayama et al., 1999; Zhang, Smith, & Witt, 2006).
		High Frequency Component of Steering Wheel Angle	⭘	Sensitive to variations in both primary and secondary task load (Östlund et al., 2004).
	Brake	Brake Reaction Time	●	Sensitive to cognitive and visual distraction. It is hard to define an event onset (Lee, McGehee, Brown, & Reyes, 2002b)
	Accelerator	Throttle Hold	●	Sensitive to visual distraction. Age factor and road type could influence this metric's sensitivity (Green et al., 2008; Zylstra et al., 2004).
Vehicle state	Lane position	SD Lane Position	●	A very common and intuitive indicator of distraction. A disadvantage could be its sensitivity to environmental factors (Jamson et al., 2004; Östlund et al., 2004; Zylstra et al., 2004).
	Speed	SD Speed	●	Speed variation was found more sensitive to visual distraction than to cognitive distraction. It could be sensitive to environmental factors (Green et al., 2008; Östlund et al., 2006; Östlund et al., 2004).
	Following time	SD Headway	⭘	This metric is sensitive to visual and cognitive distractions in car-following situations. Age could influence its sensitivity (Jamson et al., 2004; Östlund et al., 2004; Zylstra et al., 2004).

Table 1 Summary of promising metrics for distraction detection. (Continued)

Category	General indicator	Specific Indicator	Effect size	Comments
Eye/head movement	Glance frequency	Mean/SD Glance Frequency	●	Could be sensitive to both visual and cognitive distractions (Regan, Lee, & Young, 2008).
	Glance duration	Mean/SD Percent Glance Durations Off Road >2s	●	Sensitive to visual distraction (Victor et al., 2005).
	Percent of gaze on road center	Percent Road Center	●	Could be sensitive to both visual and cognitive distraction (Victor et al., 2005).
	Percent of gaze off the road	Mean/SD Percent Off Road	●	Could be sensitive to both visual and cognitive distraction (Victor et al., 2005).
	Gaze direction	SD Horizontal (Gaze or Head)	⭘	Sensitive to visual distraction (Recarte & Nunes, 2003; Victor et al., 2005)
	Gaze direction	SD Vertical (Gaze or Head)	⭘	Sensitive to visual distraction (Recarte & Nunes, 2003; Victor et al., 2005)
Physiological	Pupil	Pupil Size	⭘	Pupil size is sensitive to cognitive task performance. Intrusive sensor. (Recarte & Nunes, 2003; Recarte et al., 2008)
	Blink	Blink Rate	●	Blink rate is sensitive to both visual and cognitive distractions and can differentiate them. Intrusive sensor (Recarte et al., 2008).
	Skin conductance	GSR	⭘	Skin conductance changes during visual but not cognitive distraction. Intrusive sensor. (Östlund et al., 2006).

Note: ○ - low effect, ⭘ - moderate effect, ● - large effect

Table 2 evaluates sensors that could provide the distraction indicators in Table 1 and supports a trade-off analysis of the sensors. The various indicators on the left are described in terms of precision, robustness, timeliness, unobtrusiveness, and feasibility. Precision refers to how exactly the measure might indicate distraction. Some measures may provide only a general indication that distraction is present, whereas other measures might support a more exact differentiation of its type (e.g., cognitive or visual) and severity. Robustness refers to the degree to which a sensor will depend on the driving environment (e.g., light levels) to perform well. Timeliness is perhaps the most critical criterion. Ideally, a sensor for distraction detection would indicate the degree of distraction or need to attend to the road before the driver experiences any increased effort or diminished performance. However, some measures only provide useful information at the end of the drive. Unobtrusiveness is the opposite of intrusiveness, which refers to the degree that the sensor might annoy the driver and interfere with the drivers' ability to drive safely. Feasibility refers to the degree to which sensors can be implemented in production vehicles in a cost-effective manner. The five criteria were applied to each type of sensor using expert judgment grounded in the review of distraction-related research described in this report. Solid circles indicate more promising sensors and open circles indicate less promising sensors.

The sensor evaluation in Table 2 is based on an assessment of their performance in simulator and naturalistic driving environments. In most experiments, driving conditions were benign (e.g., daytime, clear weather, and dry road surface). Non-benign driving conditions could decrease the precision of measurement, such as when snow or rain obscures lane markings and undermines the measurement of lane position. Table 2 shows tradeoffs among sensors and depicts their ranking insofar as ideal sensors would have solid circles in all categories. Based on this criterion, steering wheel position, head tracking, eye tracking, blink, and road context emerge as particularly promising indicators and are highlighted in italic in Table 2. However, the specific choice of a sensor depends on how the strengths and weaknesses of a sensor match the mitigation strategy and how well other sensors complement it, a discussion that we turn to next.

Table 2 Promising distraction sensors as defined by precision, robustness, timeliness, intrusiveness, and feasibility.

Sensor	**Precision**	**Robustness**	**Timeliness**	**Unobtrusiveness**	**Feasibility**
	Degree to which distraction sensors index and differentiate distraction	Degree to which the sensors provide reliable data	Degree to which sensors support real-time estimates of distraction	Degree to which the sensors do not interfere with driving	Degree to which the sensor could be included in a production vehicle
*Steering wheel (position sensor)**	⊙	●	⊙	●	●
Gas/brake pedal (position sensor)	○	○	○	●	●
Event response (steering wheel and pedal input, accelerometer, and context information)	○	⊙	○	●	⊙
Longitudinal control (radar/lidar-based headway)	○	⊙	○	●	⊙
Eye movement (moderate precision eye tracking)	●	⊙	⊙	●	⊙

Table 2 Promising distraction sensors as defined by precision, robustness, timeliness, intrusiveness, and feasibility. (Continued)

Sensor	**Precision**	**Robustness**	**Timelines**	**Unobtrusiveness**	**Feasibility**
	Degree to which distraction sensors index and differentiate distraction	Degree to which the sensors provide reliable data	Degree to which sensors support real-time estimates of distraction	Degree to which the sensors do not interfere with driving	Degree to which the sensor could be included in a production vehicle
Head and body movement (low precision eye tracking and seat pan force)	◉	◉	◉	●	●
Physiological indicators (EEG, ECG, GSR)	◉	○	◉	○	○
Pupil (high precision eye tracking)	◉	○	◉	●	○
Road Context (GPS, map, other vehicles)	●	◉	●	●	◉

**Italics denote promising indicators*

Legend ○ Poor ◉ Moderate ● Good

Combining Sensors for More Sensitive Distraction Assessment

There is potential synergy between sensors and associated metrics that might produce particularly sensitive indicators of distraction. Such a synergy might produce metrics that are more precise and robust than the individual metrics in Table 2 otherwise suggest. One very promising direction concerns eye movements and steering behavior. Several studies have shown the distribution of eye movements to be sensitive to distraction and others have found steering behavior sensitive to distraction (Angell et al., 2006). Unfortunately, both are noisy signals that are influenced by many extraneous variables. The combination of these two signals has some benefits. The coordination between eye and steering wheel movements could eliminate the noise. The usage of redundant sources also allows for a continuous evaluation of driver distraction if one sensor fails. This combination can decrease the rate of false alarm: visual or manual distraction might be characterized by instances where abrupt steering responses follow an extended glance away from the road, whereas abrupt steering alone might only indicate an appropriate response to traffic.

Safety margin evaluations that consider several vehicle state data may not classify an abrupt steering performance as a distracted state if the vehicle is still in a defined safety "envelope." Combining these vehicle state data with GPS and map information, however, could detect dangerous periods of distraction that would otherwise go undetected. Because the consequence of distraction depends on both the roadway demand and the demand of the competing task, GPS and map data could provide an estimate of the roadway demand that would increase accuracy. Likewise, the eye tracker may fail to indicate the degree of distraction associated with large head or body rotations, but seat pan-based estimates of body position could be combined with eye tracker and head position data to provide a robust indicator of reaching. Just as the criteria for evaluating individual sensors are insufficient because their value often depends on combination with other sensors, criteria cannot be employed to identify an ideal combination of sensors because the value of the sensors are dependent on the algorithm and mitigation method.

Characteristics of Distraction Detection Algorithms

Algorithms to detect distraction combine the measures and integrate them over time to produce a judgment of whether or not the driver is distracted. The utility of a distraction detection algorithm depends on its compatibility with sensor data. As discussed in the previous section, although the individual measures of eye movement and steering behavior have been shown to be sensitive to distraction, there is substantial noise in the data. An algorithm that combines data may be more robust to noisy data than algorithms with no redundancy. Its utility also depends on its compatibility with the distraction mitigation it supports. For real-time feedback the algorithm must produce a sufficiently accurate and timely indication of distraction. For post-drive feedback the algorithm must be diagnostic and understandable.

To propose promising algorithms, we evaluate the properties of algorithms that have been developed to detect different types of distraction (e.g., visual, manual, and cognitive). While primarily focused on estimations of driver state, the joint demands of the roadway and competing tasks for distraction detection algorithm design are also considered. The degree to which algorithm outputs can predict impending distraction, current distraction, or summarize distraction after the event occurs in support of countermeasure considerations is also evaluated. Distinctions among the various types of distraction and the need to predict, identify, or summarize distraction have profound implications for algorithm development.

Manual, visual, and cognitive distractions are fundamentally different types of distraction that may require different algorithms. Their differences relate to both detecting and mitigating degradations in driver performance engendered through engagement with the demands of the roadway and competing tasks. Much attention has been paid to developing algorithms that address visual and cognitive distractions. The combination of different glance behavior metrics have been considered in predictive models for the risks associated with visual distraction. These algorithms allow task-independent analysis and real-time distraction evaluation. Cognitive distraction identification has proven to be more complex and requires a large amount of eye-tracking data, making it difficult to generate a continuous indicator of distraction. Reaching for a moving object – perhaps the activity with the most dangerous effect on crash/near-crash risk (Klauer et al., 2006) – has received little attention in algorithm development. The following sections summarize existing algorithms and discuss metrics for visual, manual, and cognitive distraction detection algorithm development.

Visual and Manual Distraction

Visual and manual distraction often co-occur and primarily interfere with the time eyes are directed to the road. Several approaches to estimate visual distraction as a function of eye glance pattern have been developed, including duration, history, and location of eye glances and their combination. Senders et al. (1967) developed an algorithmic approach for describing uncertainty about the driving environment as a result of glances away from the roadway, represented by occluded vision, where uncertainty grows as a 1.5^{th} power function of the occlusion duration. This algorithm accounts only for the duration of the current glances away from the roadway, which limits its ability to evaluate the effect of previous glances on driver situation awareness. To address this gap, Donmez et al. (2006, 2007) developed an algorithm based on a history of glances during a period of three seconds separately weighting current off-road glance duration and total off-road glance duration. The 100-Car Study (Klauer et al., 2006) also applied glance history in distraction estimation, but its total off-road glance duration was defined by 6-second windows. An algorithm that combined three characteristics (duration, history, and eccentricity of off-road glances) to estimate the total visual demands of a task summated the product of the 1.5^{th} power of each off-road glance duration with a penalty for glance eccentricity based on radial angle of gaze away from the forward view (Engström & Mårdh, 2007). Another penalty for glance eccentricity differentiated between driving-related (mirrors or speedometer) and non-driving tasks that require off-road glances (Kircher et al., 2009). This algorithm assumed an existence of a two-second buffer that reflects the capacity of drivers to respond. The level of buffer decreases immediately as a linear function of time when the driver looks outside the field relevant for driving (FRD). The FRD does not include off-road or driving-related glances. When the driver looks back to the FRD (on-road glance), the buffer level begins to increase as a linear function of time. A latency (adaptation period) of 0.1 second occurs with each transition from off-road glances to FRD, and a latency of 1 second occurs with transitions from driving-related glances to FRD. During a latency phase, the buffer level remains at the current position before increasing.

The ability of these algorithms to predict crash/near-crash risk was assessed using the 100-car study dataset (Liang et al., 2009). The comparison of the abovementioned algorithms and their derivatives showed that visual distraction calculation through instantaneous changes of off-road glance duration can predict crash risk. The summation of glance duration over a time-window (Donmez et al., 2007; Engström & Mårdh, 2007; Klauer et al., 2006) dilutes the signal of distraction by averaging it with non-indicative behavior. The results of the algorithm comparison suggest that the 1.5^{th} power and linearity of glance duration do not differ substantially in predicting crash risk. The eccentricity of glance location also did not substantially improve the estimation of visual distraction. Although ambient vision may help drivers maintain acceptable although somewhat degraded lane-keeping, the absence of focal vision on the roadway can result in serious impairment of hazard perception and lead to crashes/near-crashes. It also was demonstrated that the history of the glance pattern is not necessary in distraction estimation, but a short period of previous glance behavior may be important because frequent, even short, off-road glances do impair driver performance (Liang & Lee, in press). This assumption needs additional testing under different driving demands, especially for the algorithms that do not average the current glance effects with the glance history. It is also critical to identify an appropriate balance (weighting) between instantaneous and accumulative effects of off-road glances and to define an appropriate period to accumulate the contributions of previous glances to visual distraction.

Cognitive Distraction

Cognitive distraction degrades longitudinal control and hazard perception, but is less risky, more inconsistent, and more difficult to identify compared to visual distraction. Identifying cognitive distraction is more complex than visual distraction because the mechanisms involved in cognitive impairment have not been as precisely described. The detection of cognitive distraction could best occur through an integration of a number of eye movement measures (e.g., blink frequency, fixation duration, and pursuit measurements) and performance measures (e.g., steering wheel movements and lane position) summarized across a relatively long period of time. Data mining has been used to detect cognitive distraction using a large number of measures. For instance, the decision tree technique was applied to estimate cognitive workload from eye glances and driving performance measures (Zhang et al., 2004). Support Vector Machines (SVMs) and Bayesian Networks (BNs) have also successfully identified the presence of cognitive distraction using eye movements and driving performance (Liang et al., 2007a, 2007b).

One approach to detecting cognitive distraction is to assess the coherence of eye movements and steering movements. Coordination of horizontal eye movements and steering behavior has been observed, suggesting that this particular pairing may offer a robust detection algorithm. Land and Furneaux (1997) observed highly coordinated visual and steering behaviors on curvy roads during non-distracted driving, resulting in optimal performance. This coordination diminished systematically during impaired (e.g., alcohol, high stress) driving (Marple-Horvat et al., 2005, 2008) indicating that eye-steering coordination can identify the extent of driver impairment. The assessment of the degree of coordination between horizontal eye movements and steering angle also showed that it is highly consistent between drivers (Wilson et al., 2007).

The prediction of steering behavior could be achieved through eye movements, with the oculomotor controller as a transfer function. The oculomotor controller (Marple-Horvat et al., 2008) involves some neural centers that produce and control eye movements and then assist the neural centers controlling steering. This would explain why eye movements correlate with and precede steering actions. Since impairment has been shown to include changes in correlation and particularly the time lag between eye and steering movements, they promise to predict a driver's involvement in a secondary task before driving performance degrades.

Measuring the Demands of the Roadway and Competing Tasks

Distraction reflects a mismatch between the attentional demands of the road environment and the attention devoted to safety-critical driving activities (Lee et al., 2008a). The degree to which the driver's engagement in a competing activity poses a threat of distraction depends on the combined demands of the roadway and competing activity relative to the available capacity of the driver (Figure 1). Thus, distraction is a property of the joint demands of a secondary task, a roadway, and the driver's distribution of attention to meet those demands. The presence of distraction that can dramatically increase crash risk reflects an inappropriate distribution of attention between the roadway and competing activities. The situation would worsen with increasing traffic demands and/or degraded or challenging environmental conditions (bad weather, curvy road etc.), as well as when an unexpected event occurs. Thus, it is critical for the development of algorithms to consider driving conditions in evaluating a distraction impact.

The combination of driver behavior and vehicle state monitoring with road scene feature extraction could improve a distraction detection algorithm's performance in several ways. The combination enables the differentiation of inattention type. For example, eye movement data could be combined with vehicle path data to distinguish between drowsiness (e.g., eyes directed towards the road during path departures) and visual distraction (e.g., eyes directed away from the road during path departures). More nuanced parsing of inattention then supports an array of warnings (e.g., "break time" when fatigued vs. "danger" when distracted). Driver inattention is tightly connected to the inability to detect unexpected events and changes in traffic and the environment. The situation would be considered more dangerous if an obstacle is ahead when the distraction is observed. The correlation of driver eye gaze with road scene makes it possible to identify events that the driver almost certainly missed (Fletcher & Zelinsky, 2009).

Environmental factors play an important role in distraction detection algorithm performance. They differentiate between good signals and noisy signals, taking into account all other factors that can cause behavioral changes. For instance, driving in an urban area could lead to intensive eye movements not consistent with steering behavior. Changes in weather (e.g., wind gusts, heavy rain) or surface (e.g., icy road) conditions could cause changes in eye or steering movements. If an algorithm does not consider the external environment, it might classify behavioral changes as a change in driver state, when in reality they are part of the driver's reaction to changes in the environment. For example, steering movements are normally coordinated with eye glance movements, but an external disturbance such as a wind gust could induce additional steering movements that may be misinterpreted as distracted driving.

General Types of Countermeasures

The aim of detecting distraction is to support countermeasures to mitigate its effect. Consequently, a description of the general approaches to distraction mitigation is needed to support selection of measures. Some measures and algorithms are appropriate for some applications but not others. The following sections describe different theoretical perspectives regarding how the detection of distraction might be used to influence driving safety.

Cooperative automation focuses on supporting two-way communication between automation and the user rather than replacing the user with an electromechanical controller (Figure 5). In this communication, users monitor the automation to decide how it should be used (arrow 2 in Figure 5). Cooperative automation monitors user state and adapts its functions according to changing user capabilities and limitations (arrow 1 in Figure 5). For example, an adaptive collision warning system can adjust the timing of warnings based on whether the driver is attentive to the roadway or not. The system can enhance safety benefits by providing earlier warnings or reducing false alarms by delaying warnings for attentive drivers.

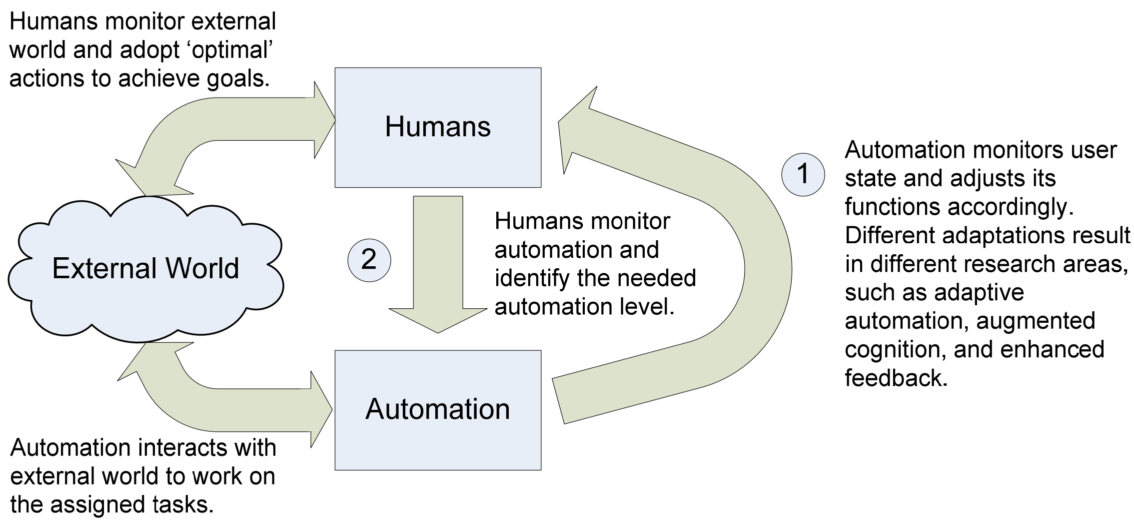

Figure 5 The relationship between human, environment, and cooperative automation (Liang, 2009).

Within the broader concept of cooperative automation several subtypes of automation can be defined: adaptive automation, augmented cognition, enhanced feedback, and attention grounding. Each emphasizes that the system can sense the state of the user, but they differ in how they adapt (or communicate) to the user (arrow 1 in Figure 5). Adaptive automation often supports supervisory control, in which the level of automation is adjusted according to the user state. For example, the system can take over tasks if users are overloaded or can return tasks to users when they are under loaded. Augmented cognition goes beyond supervisory control, by mediating information from other computers or users to avoid information overload. Enhanced feedback is an adaptive strategy that provides feedback based on the state of the user so they can adjust their behavior. Attention grounding draws upon concepts such as human-to-human communication to help drivers and the vehicle to minimize interference between roadway demands and those of the secondary task (Wiese & Lee, 2007).

Adaptive Automation and Workload Management

Adaptive automation promotes better performance by dynamically assigning tasks to either the human or the automation system 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). A summary of multiple studies demonstrated that such systems can improve human performance from 2 percent to 40 percent (Rouse, 1988).

Developing adaptive automation requires the choice of an appropriate level of automation support for efficient communication (Rouse, 1988). Three levels of automation include transformation, partition, and allocation. Transformation helps users filter and smooth information, but does not consolidate information. Partition identifies and highlights critical information to aid decision making. Allocation takes over the task completely, making decisions and taking corresponding action. The appropriate level of automation depends on the task and the state of the user. For example, if a human operator is busy with several other tasks and the new task is demanding, the automation system at the allocation or partition level could prevent the user from becoming overloaded by the tasks.

Another important issue is to identify how to communicate the state of the user to the automation system. Communication can be either explicit or implicit. Explicit communication requires the user to directly convey their state to the system. For example, the user presses a button when they think task demand is high. This kind of communication is often infeasible because it interrupts tasks and may introduce extra work. Moreover, users may be unable to provide accurate estimates of their current state. With implicit communication, the automation system collects performance data considered to implicate the state of the user. Queuing models, pattern recognition methods, control-theoretic models, and linear statistical models are then used to infer the state of the user (Rouse, 1988).

A successful example of adaptive automation was the Pilot's Associate (PA) program sponsored by the Defense Advanced Research Projects Agency (DARPA). The program developed a mission management system to enhance pilot situation awareness and decision making (St. John et al., 2004). A Pilot-Vehicle Interface (PVI) mediated the interaction between the pilot and five collaborative expert systems to create a task schedule. The PVI could infer pilot intent, share information with the expert systems, and configure the cockpit interface to display suggested activities. However, the PVI identified pilot intent through explicit communication. Although this communication method might be suitable in aviation applications, it is infeasible to use it in other domains, such as driving, because demands for training and real-time interaction are too high.

Augmented cognition estimates operators' cognitive state in real time to enhance the operator's cognitive capacity under complex and stressful conditions by adapting information display and system control (Kruse & Schmorrow, 2005). An augmented cognition system has a minimum of four components: (1) sensors, (2) an inference engine to identify user state from sensor data, (3) an adaptive interface, and (4) an underlying architecture to integrate the other components (Schmorrow & McBride, 2004).

The challenge of such systems is that in order to generate appropriate, adaptive countermeasures, they require the ability to accurately estimate operators' state. The estimated operator' state can also determine which specific channels are overloaded (e.g., visual or spatial working memory, attention etc.), which is more informative than a general workload measure. The augmented cognitive approach identifies human capability as being limited in attention, memory, learning, sensory bandwidth, visualization ability, qualitative judgments, serial processing, and decision-making. At least one of these bottlenecks needs to be identified for the system to provide a mitigation strategy. For example, the system detects impairments in visual perception and information processing that have resulted from a distracting activity. These developments closely parallel the requirements of a system that mitigates driver distraction.

Mitigation strategies provided by such systems are mostly task-oriented and can provide feedback or switch the mode of operation. However, an augmented cognition system can only benefit users if the user state is correctly inferred. The augmented cognitive program developed by DARPA examined methods to transform human-computer interaction so that systems could adapt to changing user capabilities and limitations (Schmorrow & McBride, 2004; St. John et al., 2004). The program evaluated the performance of 20 psychophysiological measures in differentiating cognitive activities. Cognitive workload was manipulated using the Warship Commander Task (WCT) as the primary task and a verbal-memory task as a secondary task. The results showed that 11 measures, including functional Near Infrared image (fNIR), electricalencephagraphy (EEG/ERP), pupil dilation, and mouse pressure, were sensitive to changes in cognitive workload. However, some of these measures are not feasible or are too costly to integrate into vehicles.

Enhanced Feedback

Enhanced feedback focuses on providing operators with information about their state so they can adjust behavior to maintain safety and efficiency. Human behavior can be described as a closed-loop control system (Sheridan, 2004). The feedback people use to adjust their behavior is largely based on self-evaluation. However, people can misjudge their performance, especially when the demands of the task exceed their capacity or when the consequences are not readily observable. Enhanced feedback provides users with an assessment of performance so the users can adjust their short-term and long-term behavior.

A fundamental law of behavior is the feedback principle that says feedback enhances performance (Holland, 1975). This is true for both task and skill learning (e.g., learning to drive safely) and for job motivation (Medsker & Campion, 1997). Direct, accurate, immediate, and continuous information on task performance is an influential way to enhance motivation and performance (Medsker & Campion, 1997). Enhanced feedback magnifies the intrinsic driving feedback that is otherwise only “partially” available (Knipling, 1999). This approach is one of positive behavioral adaptation and lifestyle change. For example, the main mechanism for increased alertness is “decision influence”, i.e. that information influences driver decisions about whether to stop for a nap, drink coffee, or reduce alcohol consumption (e.g., Knipling, 1999).

The goal of enhanced feedback is to encourage positive behavior change over multiple time-frames (adapted from Knipling, 1999):

- immediate (e.g., short-term compensatory behaviors like changing posture or aborting a complicated task)
- trip (e.g., stopping for a nap)
- day-to-day (e.g., sleeping more after a low attention day, removing video screen from front seat)
- long-term (e.g., adoption of a different sleep lifestyle or distraction attitude)

This feedback should increase driver self-awareness of inattentive behavior and enable better management. Enhanced feedback has already been shown to improve driving safety. Donmez et al. (2008b) evaluated four types of feedback: (1) real-time (milliseconds), (2) delayed (seconds), (3) retrospective (minutes, hours) and (4) cumulative (days, weeks, months) feedback. Real-time feedback reduced the secondary task engagement and increased the time drivers attended to the roadway (Donmez et al., 2007). This feedback was also more effective than other feedback strategies at reducing drivers' willingness to engage in distracting activities over time. Nonetheless, real-time feedback can be distracting. Drivers also may inappropriately rely on the feedback which can result in dangerous situations when the system fails (Donmez et al., 2007).

The other three types of feedback examined focused more on changing long-term behavior. Retrospective and cumulative feedback can be effective in training drivers. McGehee et al. (2007) examined how weekly feedback by parents changed driving behavior in teenage drivers over the course of six months. The feedback decreased the number of incidents and improvements continued after the study ended. Delayed feedback overcomes some limitations of real-time feedback, such as inappropriate reliance and extra workload. It can also guide drivers to adopt appropriate behavior, thus increasing safety (Donmez et al., 2008c). For example, the CarCoach system provided a delayed message about driver performance based on the current maneuver, driver stress, and level of driver distraction (Sharon et al., 2005). Delayed feedback helped drivers maintain smoother acceleration and achieve significantly better training results than real-time feedback. In general, enhanced feedback can provide substantial benefits in terms of both safety and efficiency.

Attention Grounding

Attention grounding was inspired by human-to-human communication, where developing common ground—a shared understanding of the other's perspective and context of the conversation—is critical for effective communication and coordination. Attention grounding builds on these ideas to reduce distraction by enhancing drivers' awareness of the attentional demands of the road and by enhancing the in-vehicle system's awareness of the attentional demands on the driver. This approach uses subtle cues from the driver (e.g., pauses in speech and variability in steering) to inform the in-vehicle system and subtle cues from the system (e.g., unobtrusive sound and vibration) to inform the driver (Wiese & Lee, 2007). Human communication is a collaborative process supported by back-channel communication (Clark & Wilkes-Gibbs, 1990; Cohen & Levesque, 1994; Goodwin, 1986). Back-channel responses (Clark & Wilkes-Gibbs, 1990; Schegloff, 1982) refer to the hearer's use of peripheral utterances, such as 'uh-huh' or 'yeah', to provide feedback that the utterance is being understood and to coordinate turn-taking (Clark & Brennan, 1991). Back-channel utterances represent a large proportion of conversations—19 percent by one estimate (Jurafsky et al., 1997)—and one might expect a similar proportion of effort spent on such indicators from in-vehicle technology. Although many speech theorists focus on back-channel communication as speech acts, back-channel communication can also take the form of pauses, intonation, gestures, and facial expressions. Back-channel responses communicate the development of a shared understanding of the situation, and thus minimize communication errors. Without back-channel communication, and its support of building shared understanding, the goals of communication are unlikely to be met and direct communication will likely fail.

As with conversation, back-channel cues support drivers' understanding of the driving situation, help coordinate the timing of interactions, and guide the adaptation of demands. Back-channel communication is already a critical component in driving. For example, drivers respond to the slippery feel of tires on an icy road to moderate their driving behavior—not just the information provided by weather reports or even focused observation of the roadway. Drivers would lose a critical component of how they sense and perceive the driving environment if they did not have such back-channel cues. Although the ideas of back-channel communication were initially developed to describe communication between people, the concepts are relevant to any situation that demands dynamic coordination between multiple entities (Brennan, 1998).

Applied to distraction prevention and mitigation, attention grounding could provide another means by which driver distraction is detected. For example, a system utilizing attention grounding might use the pauses between voice commands of the driver to identify situations where the driver should attend to a demanding driving situation.

Table 3 summarizes the general approaches for distraction mitigation, with solid circles indicating that the system performs well on a given dimension. Some of these characteristics are more consistent with the driving domain than others. The ratings of this table represent the authors' rough estimate of how each system compares to the others for each dimension based on the preceding discussion of each approach. From this evaluation, the most promising distraction mitigation system is enhanced feedback that could indicate distraction and increase driver self-awareness and distraction management skills at several time scales (real-time vs. long term). An enhanced feedback algorithm would provide both real-time assessment (predictiveness) of driver state and summary information (informativeness) about the associated driving performance. Simplicity may also play an important role in that it describes the degree to which the driver can interpret the system output. Although information about changes in blink or heart rate may be useful measures for detecting distraction, their application in a detection algorithm are not easily communicated and drivers might not understand the meaning of feedback based on these signals. On the other hand, information about head and body movements could be found very informative and easily understood.

Table 3 Distraction mitigation approach summary.

		Adaptive automation	**Augmented cognition**	**Enhanced feedback**	**Attention grounding**
Simplicity	Degree to which the system behavior is understandable	◎	○	●	●
Distinctness	Degree of system's precision in differentiating operator state	●	●	◎	◎
Autonomy	Degree to which the system adjusts its function to the user state	○	●	○	◎

Immediacy	Degree to which system influences immediate behavior	◉	◉	◉	○
Predictiveness	Degree to which system can predict distraction	●	●	◉	○
Informativeness	Degree to which information can be implemented for future revision	○	○	●	●
	Legend	○ Poor	◉ Moderate	● Good	

Countermeasure Considerations in Sensor and Algorithm Selection

Driver distraction can be regulated in different ways: providing feedback to the driver to induce positive behavioral changes, identifying distraction to warn a driver, and designing distraction prediction systems. Timeliness and accuracy are perhaps the most critical criteria in choosing sensors to support distraction prediction and identification. An accuracy requirement assumes that a combined driver-vehicle-environment system should be considered. For post-driving feedback, it is more important to consider an algorithm that informs drivers of degradations while distracted, and provides a means through which behavioral changes can be identified (simplicity and informativeness). This section summarizes approaches used in previous developments of mitigation systems.

Two research projects, DRIVE (Dedicated Road Information Infrastructure for Vehicle safety in Europe) and PROMETHEU.S., used elements of cooperative automation to enhance driving safety (Emberger, 1993; Gerhardt, 1993). The DRIVE project provided drivers information, advice, and guidance to optimize traffic flow across different locations and time (Gerhardt, 1993). The study produced a prototype and assessed the performance of "Generic Intelligent Driver Support" systems, specifying how such systems could fit into driving and how they changed the behavior of drivers. The PROMETHEUS program focused more on maintaining safety for an individual vehicle (Emberger, 1993). The system used in-vehicle sensor technologies to monitor roadway conditions, local traffic parameters (e.g., headway time), and vehicle state, in order to provide advice, warn drivers, assist driver decision making, and intervene to control the vehicle during emergency situations. The PROMETHEUS system was adaptive, but had a high rate of false alarms and was not accepted by drivers. This may have occurred in part because the system did not consider the state of the driver.

Recent research programs, such as HASTE (Human machine interface And the Safety of Traffic in Europe) and AIDE (Adaptive Integrated Driver-vehicle InterfacE) have considered systems that adapt to the state of the driver. The major objective of the HASTE program was to develop methodologies and guidelines for assessing visual and cognitive distraction caused by different in-vehicle information systems (IVISs) (Carsten et al., 2005). Driver performance was examined 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 event detection to evaluate the cognitive load of IVISs, but because of the high workload associated with this task it is not suitable for assessing drivers' cognitive state in real-time systems. The AIDE program focused on how adaptive technologies could be used to integrate different in-vehicle support systems. The mental workload induced by visual and cognitive distractions was investigated through vehicle control metrics (Östlund et al., 2005). The program focused on: (1) modeling relationships between drivers, vehicles, and environment; (2) investigating driver adaptation to the in-vehicle support devices; (3) creating guidelines and technology for in-vehicle information system design; and (4) evaluating the risk of using in-vehicle support systems. However, the AIDE program, like HASTE, was unable to unobtrusively assess driver cognitive distraction in real-time.

NHTSA sponsored a program to develop a test vehicle incorporating adaptive interface technology, SAfety VEhicle using adaptive Interface Technology (SAVE-IT) (Witt, 2003). The goal of this program was to develop and demonstrate a system to mitigate distraction. One part of the SAVE-IT project focused on creating a system that inferred driver state from sensor data to control information flow of in-vehicle systems to drivers. 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 industry standards needed to achieve widespread application of a common adaptive interface.

The driver distraction mitigation system in the SAVE-IT program also sought to diminish overload caused by drivers' engagement in distracting tasks and to guide driver behavior to maintain safety (Figure 6). Distraction was identified using visual behavior, vehicle control input, and vehicle kinematics demonstrating that it is possible to detect distraction unobtrusively in real-time.

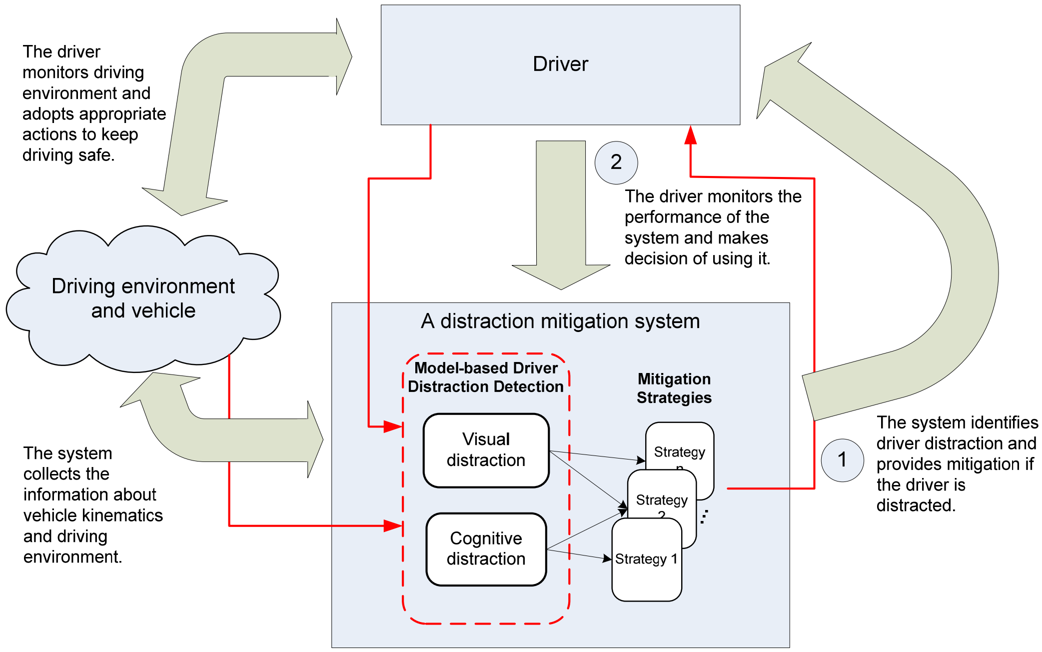

Figure 6 A distraction mitigation system in the context of cooperative automation (Liang, 2009).

Table 4. Summary of Indicators of Distraction

Category	General indicator	Specific Indicator	Description	Comment	Source
Eye/head movement	Glance frequency	[Mean or Standard Deviation or Total]_Glance_Frequency_[Gaze or Head]_TargetX	Number of glances to a target within a pre-defined time period, or during a pre-defined task, where each glance is separated by at least one glance to a different target (off road, zone X, cluster X). A target is a pre-determined area within the visual scene, e.g. a rear-view mirror.	Uses either Areas-of-Interest (zones) or clusters to find target areas. Because it uses an area of interest, it is less robust.	ISO (2002)
	Glance duration	[Mean or Standard Deviation or Total]_Glance_Duration_[Gaze or Head]_TargetX	Time from the moment at which the direction of gaze or head moves towards a target (e.g. the interior mirror) to the moment it moves away from it.	Uses either Areas-of-Interest (zones) or clusters to find target areas. Because it uses an area of interest, it is less robust.	ISO (2002)
		[Mean or Standard Deviation]_Percent_Glance_Durations_>2s_[Gaze or Head]_TargetX	The percentage of glances to a target that have a duration longer than two seconds	More sensitive than Glance Duration	Victor, Engström and Harbluk (2005), HASTE, AIDE
	Percent of gaze on road center	[Mean or Standard Deviation]_Percent_Road_Centre_[Gaze or Head]	The percentage of gaze or head direction data points during a fixed time period that fall within a road center area. The road center area is defined as an area (e.g. 8 degree radius for gaze, head will considered in future algorithms) centered around the road center point. The road center point is determined as the most frequent gaze/head angle, e.g. using mode or mean to find the peak in a 2D histogram of gaze/head data during a period (of at least 1 minute) of driving.	Uses a cluster-driven (bottom-up) calculation is likely more robust than target-area-driven calculation. Validated and recommended in HASTE and AIDE EU projects.	Victor, Engström and Harbluk (2005), HASTE project, AIDE project, Victor and Larsson (2005)

Category	General indicator	Specific Indicator	Description	Comment	Source
	Percent of gaze on off the road	[M/SD]_Percent_Off_Road_[Gaze or Head]	Percentage of gaze or head direction data points which are focused off the road (driving scene). Is simply the inverse of Percent Road Centre	Could use distance driven during an off road glance?	Various e.g. 100-car, (Victor et al., 2005); Victor and Larsson (2005)
	Time sharing periods	[Mean or Standard Deviation or Total]_Visual_Time_Sharing_[Gaze or Head]_TargetX	Number of periods of visual time sharing behavior (glancing back and forth between the road center and e.g. a navigation system).	2 algorithms exist	Victor and Larsson (2004) and AIDE
	Intensity of time sharing	[Mean or Standard Deviation or Total]_Visual_Time_Sharing_Intensity_[Gaze or Head]_TargetX	The intensity of the visual time sharing behavior. Expressed as percentage of visual time sharing period spent with eyes on road center (as opposed to eyes-off-road). Measure of the intensity of the visual time sharing.	New idea, algorithms to be developed	
	Duration of time sharing	[Mean or Standard Deviation or Total]_Visual_Time_Sharing_Duration_[Gaze or Head]_TargetX	The duration of the visual time sharing behavior. Expressed as the number of seconds spent with visual time sharing away from the road center.	New idea, algorithms to be developed	
Eye/head movement (continued)	Gaze direction	[Mean or Standard Deviation or Total]_Visual_Direction_[Gaze, Head]_TimeY	Gaze or head direction at a point or segment of time (Y)	E.g. gaze direction just before a warning is given by an ADAS	Dingus et al (2005)
		[Mean or Standard Deviation]_Standard_Deviation_Horizontal_[Gaze or Head]	Standard deviation of the horizontal gaze or head direction signal	Measures "reduction of environmental intake", i.e. horizontal scanning distribution	(Recarte & Nunes, 2003); (Victor et al., 2005), HASTE, AIDE
		[Mean or Standard Deviation]_Standard_Deviation_Vertical_[Gaze or Head]	Standard deviation of the vertical gaze or head direction signal	Measures "reduction of environmental intake", i.e. vertical scanning distribution	(Recarte & Nunes, 2003; Victor et al., 2005); HASTE; AIDE

Category	General indicator	Specific Indicator	Description	Comment	Source
		[Mean or Standard Deviation]_Standard_Deviation_Radial_[Gaze or Head]	Standard deviation of radial gaze (or head direction), the vector sum of horizontal and vertical gaze (or head direction) components. That is, the square root of the sum of squared vertical and squared horizontal angles. It is a one-dimensional angle between the zero intercept and gaze point.	Measures general "reduction of environmental intake". Is more sensitive but less diagnostic than horizontal and vertical gaze.	(Victor et al., 2005), HASTE, AIDE
		[Mean or Standard Deviation]_Standard_Deviation_Radial_External_[Gaze or Head]	Standard deviation of radial gaze when glances toward the vehicle interior target area are removed from the data.	Measures "reduction of environmental intake" during in-vehicle tasks. Useful because it removes glances to the interior.	Victor and Johansson (2005)
		Long_Single_Glance_[Gaze or Head]	Length of a long single glance		
	Head Position	[Mean or Standard Deviation or Total]_Global_Head_Movement	The sum of all head rotations and translations. A-F are weighting factors which determine the sensitivity for different types of movements	Large amounts of head movement can indicate high workload, e.g. changing lanes, at an intersection.	(Victor & Larsson, 2004)
		[Mean or Standard Deviation]_Reversal_Rate_Head	Reversal rate of head movements.	Large amounts of head movement can indicate high workload, e.g. changing lanes, at an intersection. Algorithm.	
		Head_Position_[x, y, z]	Head position in 3 dimensions		
		[Mean or Standard Deviation]_Percentage_Eye_Closure	Percentage eye closure measure (calculated by eyetrackers)		Wierwille (199X)

Category	General indicator	Specific Indicator	Description	Comment	Source
		[Mean or Standard Deviation]_Vision-Action_Coordination	Integration of visual behavior measures with the effect they have on lateral and longitudinal control measures.	New idea, algorithms to be developed	
		[Mean or Standard Deviation or Total]_Blink	Blink-related measures might have potential application as a part of future algorithms		
Driver control input	Brake	Brake_Application	The number of times the brake applied with brake lights application.		(ref. byWierwille et al., 1996)
		[Mean or Total] Brake_Application_Time	The total time that the brakes were applied and made brake lights on.		ref. by Wierwille et al. (1996)
		Brake_Reaction_Time	The reaction time to the braking event	It is more critical to consider brake reaction time than the components (Accelerator-Release Time and Accelerator-to-Brake Transition Time) because of driver compensatory behavior. In the real world conditions, it is hard to define a reliable brake reaction time because of event onset identification issue.	Lee et al. (2002); ref. by Wierwille et al. (1996)
		Brake-to-Maximum Brake Transition Time	Time required by the driver to reach maximum deceleration after the initial depression of the brake pedal		Lee et al. (2002)

Category	General indicator	Specific Indicator	Description	Comment	Source
		[Mean or Maximum]_Deceleration	Mean deceleration is defined as the average deceleration of the vehicle from initial brake depression until the driver's vehicle stops, collides with the lead vehicle, or passes the lead vehicle. Maximum deceleration is defined as the peak deceleration between the beginning and end of the braking event.		Lee et al. (2002)
		Brake_Jerks	Number of abrupt onsets of the brakes during driving	Since there most likely will be very few abrupt brake onsets, this metric will seldom produce significant results.	Ostlund et al. (2006), AIDE
		Reaction_Time	The time the subject initiated a braking or evasive manoeuvre in response to the critical event, minus the time critical event initiation.	Reaction time is used to measure distraction or workload. It is hard to define reaction time because of event onset identification issue.	Jamson et al. (2004), AIDE
Driver control input (continued)	Accelerator	Accelerator-Release Reaction Time	Time from lead vehicle braking onset to accelerator release		Zhang et al. (2006); Lee et al. (2002)
		Accelerator-to-Brake Transition Time	Time between driver release of the accelerator and application of the brakes		Lee et al. (2002)
		[Standard Deviation] Accelerator	Standard deviation of accelerator displacement.		Dingus et al. (1989)
		Accelerator_Release	The number of times that the accelerator is returned to the undeflected position for t seconds or longer.		ref. by Wierwille et al. (1996)
		[Mean or Total] Accelerator_Release_Time	The mean (or total) that the accelerator is in undeflected position.		ref. by Wierwille et al. (1996)

Category	General indicator	Specific Indicator	Description	Comment	Source
		Accelerator_Hold	The number of times that the magnitude of accelerator velocity remains at or below the defined value for T second or longer.		ref. by Wierwille et al. (1996)
		Throttle_Hold	Duration of time (time window) in which the maximum minus the minimum throttle opening does not exceed some value (threshold).	Throttle holds are more frequent for normal driving than for distracted driving. This result was found opposite to the results from Zylstra et al. (2004), and the reason that was mentioned was difference in resolution (low vs. high) of throttle opening.	Green et al. (2008), SAVE_IT, Zylstra et al. (2004), SAVE-IT
		[Mean or Total] Accelerator_Hold_Time	The mean or total time of accelerator holds.		ref. by Wierwille et al. (1996)
		Throttle_Percent	Proportion of throttle correction periods and no throttle correction periods.	Sensitive to performing in-vehicle tasks.	Zylstra et al. (2004), SAVE-IT
		[Standard Deviation]_Throttle Position or Opening		Standard Deviation was greater when either looking away or performing a task than for the baseline driving condition. Correlated with speed.	Zylstra et al. (2004), SAVE-IT; Green et al., (2008), SAVE-IT
		[Mean or Standard Deviation or Maximum or Minimum]Heading_Angle		Correlated with Steering Angle	Green et al., (2008), SAVE-IT

Category	General indicator	Specific Indicator	Description	Comment	Source
Driver control input (continued)	Steering wheel	[Standard Deviation]_Steering_Wheel_Angle		This metric is commonly used in evaluation of cognitive and visual distractions. It is sensitive to variation in the steering wheel data especially at lower frequencies and can make confusion with road curvature and maneuvers.	Zylstra et al. (2004), (SAVE-IT); Green et al., 2008 (SAVE-IT);
		[High Frequency Component] Steering_Wheel_Angle	Spectral power of the 0.3-0.6 Hz component of the steering wheel angle variations.	This metric is sensitive for visual distraction.	Östlund et al. (2004)
		Steering_Wheel_Reversal_Rate	The number of times that the steering wheel is reversed by a magnitude larger than a specific angle, or gap.	Steering Wheel RR (with gap sizes between 0.5 and 5 deg.) correlated strongly with HFC. This metrics is commonly used because of simplicity but it is sensitive to environmental factors.	Östlund et al. (2004); Green et al., 2008 (SAVE-IT)
		Rapid_Steering_Wheel_Turns	The number of times that the steering wheel is reversed by a magnitude of the defined deg/s velocity thresholds.	The metric with threshold of 5 and 10 deg/s showed sensitivity to visual distraction. The environmental, task difficulty, and age factors could affect the sensitivity of the metric.	Östlund et al. (2004)
		Steering entropy	Calculated on the basis of prediction errors of steering signals (by performing a second-order Taylor expansion). Entropy of the signal is then calculated on through the errors distribution.	Steering entropy is affected by task and has a high correlation with glance metrics. Not intuitive but could be promising.	Nakayama et al. (1999); Boer (2000); Zhang et al. (2006)
		[Maximum]_Peak_Steering_Deflection	The maximum magnitude of steering deflection from fixed position.		ref. by Wierwille et al. (1996)
		[Mean or Standard Deviation]_Steering_Velocity		Metrics were sensitive to drowsiness and alcohol impairments.	Dingus et al. (1989)

Category	General indicator	Specific Indicator	Description	Comment	Source
		Number_Steering_Holds	Number of times that the magnitude of steering velocity remains below constant value for at least some duration.		ref. by Wierwille et al. (1996)
		Steering_Zero_Crossings.	Number of times that steering displacement passes through zero.		ref. by Wierwille et al. (1996)
		Steering_Holds	Periods of at least 400 ms involving no steering activity	Steering holds are significantly fewer in the higher workload conditions. Could be correlated with other steering metrics, e.g. SD steering angle, steering entropy, etc.	Ranney et al. (2005)
		Hands-on-Wheel_Occurrences	The number of times that the driver places both hands on the wheel without changing hand positions		Tijerina et al. (1996)
		[Mean]_Hands-on-Wheel_Duration	The mean length of time that the driver places both hands on the steering wheel without changing hand positions		ref. by Wierwille et al. (1996)
		Total_Time_Hands-on-Wheel	The total time that both of the driver's hands are in contact with the rim or spokes of the steering wheel		ref. by Wierwille et al. (1996)
Vehicle state	Lane position	[Mean or Standard Deviation] Lane_Position	Mean (Standard deviation) value of vehicle lateral position measured from the centerline.	A very common indicator of distraction and is reported by most experiments addressing driver distraction. The disadvantage is that it is sensitive to environmental factors.	Östlund et al. (2004), HASTE; Jamson et al. (2004), AIDE; Zylstra et al. (2004), SAVE-IT
		[Root_Mean_Square of Standard Deviation] Lane_Positioning	Square root of the average squared deviation in lane position about the mean lane position observed during a task.	Sensitive to some environmental conditions (e.g., wind gust disturbances)	ref. by Wierwille et al. (1996)

Category	General indicator	Specific Indicator	Description	Comment	Source
		Peak_Lane_Deviation	The maximum value between vehicle and lane centerlines.	Sensitive to some environmental conditions (e.g., wind gust disturbances)	ref. by Wierwille et al. (1996)
		Lane_Exceedences	The proportion of a time that any part of the vehicle is outside the lane boundary OR the number of times that the vehicle exceeds lane boundaries	This metric has higher validity than lane variation measures (e.g. standard deviation). However, it may be insensitive to small shifts in workload or distraction.	Dingus et al. (1989), Östlund et al. (2004), HASTE; Zhang et al. (2006)
		[Mean] Lane_Exceedence_Duration			ref. by Wierwille et al. (1996)
		[Mean or Minimum] Time_Lane_Crossing	TLC is time to reach the lane marking assuming fixed steering angle and constant speed	TLC is correlated with Lane Position metric	Östlund et al. (2004), HASTE
		[Mean of Minimum] Time_Lane_Crossing			Östlund et al. (2004), HASTE
		[15%-ile] Time_Lane_Crossing	15 percentile of the TLC values	There is a correspondence between TLC and driver's self-chosen occlusion times.	Godthelp et al., (1984)
	Speed	[Mean, Standard Deviation, Maximum, or Root Mean Square Deviation] Speed	The average of the longitudinal speed relative to the road surface.	Drivers adapt their speed to the driving conditions. Speed variation was found more sensitive to the visual distraction than for the cognitive.	Östlund et al. (2006); Östlund et al. (2004), HASTE; Zylstra et al. (2004), SAVE-IT; Green et al., 2008, SAVE-IT
	Following time or distance	[Mean, Standard Deviation, or Minimum] _Headway	Time gap between lead and subject vehicles. Headway values larger than 3 sec or 50m are ignored.	This metric is sensitive for visual and cognitive distractions in car-following situations. The effects were more substantial for elderly drivers.	Östlund et al. (2004), HASTE; Jamson et al. (2004), AIDE; Zylstra et al. (2004), SAVE-IT

Category	General indicator	Specific Indicator	Description	Comment	Source
Vehicle state (continued)	Following time	[Minimum] Time_To_Collision	Time to collision if the vehicle continues to travel at their current relative position, velocity, and acceleration. TTC values larger than 15 seconds are ignored	This metric is correlated with headway and could be used to measure the severity of the collision. It was used to evaluate effect of the safety systems.	Östlund et al. (2004), HASTE; Lee et al. (2002)
		Time Exposed TTC (TET)	The proportion of time of which the TTC is less than X seconds		Östlund et al. (2004), HASTE
	Following distance	Coherence	A measure of the correlation between the speed profiles of following and lead cars		Brookhuis et al. (1994); Janacek (2008)
		Phase shift or Delay	An index of the delay between the speed profiles.		Brookhuis et al. (1994); Janacek (2008)
		Modulus or Gain	This quantifies the amplification between the two signals and identifies “overreactions” or "underreactions" of the following vehicle.		Brookhuis et al. (1994); Janacek (2008)
Physiological	EEG	Electroencephalography	Power spectra of Alpha, Beta, and Theta bands for each channel or segment	It allows discriminating human cognitive activity correctly for different tasks. The sensors are intrusive.	St. John et al., 2006
	ECG	[Mean/Standard Deviation] Heart_Period or Heart_Rate	The time in milliseconds (or number of beats per minute) between successive R-peaks	There is a correlation between heart rate metric with continuous driver stress levels. The sensors are intrusive.	Lenneman et al., 2005; Östlund et al. 2006
		[Mean/Standard Deviation] Pre_Ejection_Period	Sympathetic index is the first derivative of pulsatile changes in transthoracic impedance	Was not found sensitive to the task difficulty. The sensors are intrusive.	Lenneman et al., 2005

Category	General indicator	Specific Indicator	Description	Comment	Source
		[Mean/Standard Deviation] Respiratory_Sinus_Arrhythmia	Parasympathetic index is measured from high frequency heart rate variability (0.14-0.40 Hz)	Was not found sensitive to the task difficulty. The sensors are intrusive.	Lenneman et al., 2005
	Pupil	[Mean/Standard Deviation] Pupil_Diameter	Pupil size is measured in pixels.	Pupil size is sensitive to mental workload changes. It does not differentiate cognitive and visual workload.	Recarte & Nunes, 2003, Recarte et al., 2008
	Eye	Blink_Rate	The number of times per minute that the eyelid automatically closes.	Blink rate is sensitive to both visual and cognitive distractions. It can differentiate cognitive and visual tasks.	Recarte et al., 2008
	GSR	Galvanic skin responses or skin conductance responses	It was extracted as the 0.05 Hz to 2.00 Hz component of skin conductance recording	Significant changes in skin conductance were found for visual distraction but not for cognitive	Östlund et al. 2006

Appendix B: Select Narrative Descriptions of Distraction and Mitigation Systems

Volvo's Driver Alert Control

Status: Production

Models:[1]
2008/2009/2010 Volvo S80, V70, XC70, Collision Avoidance Package with Driver Alert System (DAC & LDW) (U.S.)
2009 Volvo XC90, Technology Package (U.S.)
2010 Volvo XC60, Technology Package (U.S.)
2010Volvo XC70, Technology Package (U.S., N.Z.)
2010 Volvo S80, Technology Package (U.S.)

Textual description
The Volvo Driver Alert Control (DAC) system is a drowsiness detection and mitigation system that provides safety benefits for distracted drivers. Instead of evaluating the driver for signs of fatigue or decreased concentration (e.g., eye movement behavior), the DAC assesses the effects of fatigue and decreased concentration on driving behavior [1]. This approach is based on two premises: (1) human behavior is too varied and the technologies available during the system's development too unreliable for a driver-state-based system to work with sufficient accuracy and reliability, and (2) evaluating the progress of the vehicle on the road provides an accurate and reliable indication that fatigue or decreased concentration are hindering driving performance. Volvo claims that the design of the DAC allows for it to issue alerts before extreme fatigue severely affects driving by learning driving patterns and predicting the correct path [2], then issuing alerts when deviations occur between the vehicle's actual path and that predicted by the system. The underlying assumption of the invention's design is that impaired drivers cannot estimate and adapt driving to the upcoming road situation as accurately as an alert driver can. The basic variable for the operation of the system is the distance between the car and road lane markings.

To assess if the vehicle is driven in a controlled or uncontrolled way, this system uses (1) planned path computation (path expected to follow from first instant considering the state of the vehicle at the first instant), and (2) adaption of time horizon; planned deviation computation (determining the planned lateral position of the vehicle in relation to a lane at a second instant being a time interval after t1 if planned path were followed, then determining a planned deviation, the difference between the planned lateral position at second instant and the lateral position at first instant) [3].

This system uses mean planned deviation computation (a number of planned deviation measures calculated at subsequent instants that are then used for evaluation). Planned

[1] Regions listed after each model and production year have been verified; the lists of regions are not, however, comprehensive. In cases where no link between specific regions and models/years could be made, general regional information is provided.

deviation measures are compiled by forming a mean over the planned deviation measures; for impaired drivers, MPD values tend to increase over time, whereas alert drivers' values remain constant [4].

Driver state is categorized in two ways: if the planned deviation measures/MPD measures exceed a threshold, or repeatedly exceed the threshold during a certain time interval [4], (1) a 5-bar rating shows cumulative assessment of driving, and (2) auditory and text message (coffee cup) alerts appear as an absolute measure of drowsiness.

The DAC consists of a camera (mounted between the windshield and rear-view mirror, looking forward), a number of sensors (which register the vehicle's movements), and a control unit (which stores the information and calculates whether the driver risks losing control of the vehicle) [5]. The vision-based system is supplied by Mobileye N.V. A processor in the camera system analyzes the video stream, applying Mobileye's lane and vehicle detection algorithms, which allows the Volvo functional algorithms to analyze the vision data along with the data collected from sensors recording data from the vehicle. Information streams include vehicle data (vehicle speed, yaw rate); environmental data (vehicle position, road geometry, stationary objects (lane markings), dynamic objects (vehicles); and interaction data (not specified) [4]. The combination of data is used to determine the driver's state (alert or not). The vehicle detection algorithm allows the DAC to analyze the driver's behavior relative to traffic; Mobileye claims that this enables the system to produce a more accurate assessment of the alertness level and reduces the number of false alarms by comparing the driver's maneuvers with those of surrounding traffic. Mobileye's lane detection technology measures the distance between the vehicle and the lane markings. The DAC stores the information and calculates, in real-time, whether the driver risks losing control of the vehicle. It should be noted however, that this contradicts the patent description attributed to the production version of the DAC, which claims that nothing is done in real-time [6].

The system is designed for driving environments where the risk of drowsiness is the greatest, such as smooth, straight roadways at higher speeds (it is triggered at about 40 mph and remains activated until the speed drops below 37 mph). Volvo's 2005 press release describes the system's mitigation as two separate components: an audible signal and a text message that appears in the information display if driving patterns suggest high risk, and a 5-bar rating of the consistency of the driver's performance. The system is also explicitly differentiated from a lane departure warning system; the DAC supposedly responds even if the lane has not been exceeded [7]. The functionality of the DAC is dependent on the visibility and quality of the road markings. Worn or non-existent markings or poor light, fog, snow, or other extreme weather conditions can lead to the DAC not working [8].

References

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Volvo's Driver Alert Control Related Research Concepts

Status: Development

Textual description
Volvo is developing a new version of its fatigue and distraction detection system based on advances in eye movement detection technologies. In partnership with the Australian National University, Volvo founded Seeing Machines in order to develop a dual-camera-based system for more reliable tracking of a driver's eye movements [1, 2, 3]. The system has been further developed in Volvo's Safety Car Concept, which has focused on using an eye sensor to identify drowsy drivers [4]. Some recent studies make an effort to design an algorithm that will combine eye pattern and driving performance [5, 6] by considering eye movement as part of attention assessment. Algorithms analyze driver reactions to movements of other vehicles taking into account gaze direction and monitoring the distance from the lane markings. The system in development is designed to determine vehicle positioning and whether driver responses match those of an alert or a distracted behavior.

The system in development continues to evaluate large-time-scale driving patterns for signs of diminished driver state, but supplements this with an evaluation of driver state. The system considers driver ocular and head orientation characteristics relative to the environment. The algorithm is based on estimation of glance frequency, single glance duration, total glance time, and total task time in the predetermined time window with the reference to the base head/eye position. The concepts of Percent Road Center (PRC) and Absolute Percent Road Center (A-PRC) as measures of driver attentiveness to the road ahead were utilized. Through the observed eye activity, the system can identify drowsiness conditions. The system is designed to analyze drivers' reactions to movements of other vehicles in the vicinity by determining vehicle positioning and monitoring driver gaze direction, in order to assist in determining whether driver responses match those of an alert or distracted driver. It utilizes a camera placed in the steering wheel area to capture driver state and another camera placed between the windshield and the interior rear-view mirror to capture identifying lane markings and other vehicles. The control unit (CAN data bus) stores the information and calculates whether the driver risks losing control of the vehicle. The camera-based system detects a blink of the eyelid by means of a camera frontally placed in the steering wheel area and calculates the eyelid blink frequency and the eyelid blink duration. Another camera, placed between the windshield and the interior rear-view mirror, views the scene ahead, identifying lane markings and other vehicles. The sensors register the car's movements. The control unit stores the information and calculates whether the driver risks losing control of the vehicle.

The performance of the system depends on the visibility and quality of the road markings. Poor light, fog, snow, and extreme weather conditions can make the feature unavailable. Seeing Machines claims that current iterations of the system are not affected by the driver wearing eyeglasses or sunglasses or by varying light conditions in the vehicle [2]. The Driver Alert system operates at speeds from 65 km/h [2]. Lane Departure

Warning and Driver Alert Control are parts of the Driver Alert package. The system rates driver attentiveness on a scale of one to five based on the following outputs: glance frequency (the number of glances toward a target area during pre-defined time period), single glance duration, total glance time, and total task time. A caution warning would be provided to driver. The driver could be able to choose up to three warning versions: visual with different icons (eye closure, inconsistent steering or lane-keeping), audible, and/or physical stimulation [1].

References

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Appendix C: Specification Template for Distraction Detection and Mitigation

Introduction

The tables on the following pages represent the short template form used to provide information about distraction detection and mitigation systems. A key for the template is also included.

The first section of the form, labeled Detection-Purpose, is intended to gather information about what the distraction detection system was designed to do. The Input section allows users to indicate the operating conditions under which the system works, the Transformation section allows users to indicate which mitigation strategies are used, and the Output section allows users to indicate which countermeasures are supported.

The second section of the form, labeled Detection-Function, is intended to gather information about the functional means of achieving the system's purpose. The Input section provides information about driver and vehicle information streams, the Transformation section allows users to indicate which information combinations and algorithms are used, and the Output section allows users to indicate which driver states are detected and how they are resolved.

The third section of the form, labeled Countermeasure-Purpose, is intended to gather information about how the system mitigates distraction.

The fourth section of the form, labeled Countermeasure-Function, is intended to gather information about the mechanism by which the system undertakes specific approaches to mitigate the driver's engagement with distracting tasks.

The form also presents a way to distinguish between machine learning and other algorithm details under the Functional Transformation section for Detection.

The template entries for production systems and concepts include only applicable sections, e.g., if the specification only describes a detection algorithm, it will only include the first and second sections describing the detection system's purpose and function.

Manufacturer: Volvo

System Name: Driver Alert Control

Model Year: 2008/2009/2010 S80, V70, XC70 (U.S.), 2009 XC90 (U.S.)
2010 XC60 (U.S.), XC70 (U.S., N.Z.), S80 (U.S.)

☐ **Aftermarket** *or* ☒ **OEM**

☒ **Production** *or* ☐ **Research**

☒ Standard configuration ☐ Reconfigurable Notes:

Detection - Purpose

Input	Applicable?			Requirement					Notes
Road Conditions	☒ Yes	☐ No	☐ Unknown	☒ Good visibility	☒ Visible Road Markings	☒ High Speed Roads	☐ _____	☐ _____	
Vehicle Interior	☐ Yes	☒ No	☒ Unknown	☐ Ambient Illumination	☐ Sound Level	☐ _____	☐ _____	☐ _____	
Vehicle State	☒ Yes	☐ No	☐ Unknown	☒ Speed	☐ Traffic Demand	☒ Imminent Collision	☒ Lane Marking	☐ _____	system activated at speeds > 40 mph, remains active until speeds < 37 mph
Driver	☐ Yes	☒ No	☐ Unknown	☐ Head Position	☐ Glance	☐ Posture	☐ _____	☐ _____	
________________	☐ Yes	☐ No	☐ Unknown	☐ _____	☐ _____	☐ _____	☐ _____	☐ _____	

Transformation	Applicable?			System Type					Notes
Derivative System	☒ Yes	☐ No	☐ Unknown	☒ Drowsiness Fatigue	☐ CWS	☐ _____	☐ _____	☐ _____	
Detection Approach	☒ Yes	☐ No	☐ Unknown	☐ Visual Search	☒ Vehicle Control	☐ _____	☐ _____	☐ _____	
________________	☐ Yes	☐ No	☐ Unknown	☐ _____	☐ _____	☐ _____	☐ _____	☐ _____	

Output	Applicable?			Supported					Notes
Driver State	☒ Yes	☐ No	☐ Unknown	☐ Visual Distraction	☐ Cognitive Distraction	☒ Inattention	☐ _____	☐ _____	Inattention: fatigue and drowsiness distraction detection as a byproduct
________________	☐ Yes	☐ No	☐ Unknown	☐ _____	☐ _____	☐ _____	☐ _____	☐ _____	

Manufacturer: Volvo **Model Year:** 2008/2009/2010 S80, V70, XC70 (U.S.), 2009 XC90 (U.S.) / 2010 XC60 (U.S.), XC70 (U.S., N.Z.), S80 (U.S.)

[ ] **Aftermarket** *or* [X] **OEM**

System Name: Driver Alert Control

[X] **Production** *or* [ ] **Research**

Detection - Function

Input	Applicable?	Information Streams	Notes
Driver Data	[ ] Yes [X] No [ ] Unknown	[ ] Pupil [ ] Eye Gaze [ ] Head Pose [ ] ___ [ ] ___	
Vehicle Data	[X] Yes [ ] No [ ] Unknown	[X] Longitudinal Control [X] Lateral Control [ ] CWS [ ] ___ [ ] ___	
Environmental Data	[ ] Yes [X] No [ ] Unknown	[ ] GPS Location [ ] Headlights [ ] ___ [ ] ___ [ ] ___	
Task Data	[ ] Yes [X] No [ ] Unknown	[ ] Audio Status [ ] Phone Status [ ] IVIS Status [ ] ___ [ ] ___	
___	[ ] Yes [ ] No [ ] Unknown	[ ] ___ [ ] ___ [ ] ___ [ ] ___ [ ] ___	
___	[ ] Yes [ ] No [ ] Unknown	[ ] ___ [ ] ___ [ ] ___ [ ] ___ [ ] ___	

Transformation	General Algorithm Information
Algorithm	Machine Learning? [ ] Yes [ ] No [X] Unknown — *Notes:* Planned deviation measures (MPD) are compiled by forming a mean over the planned deviation measures. If this measure exceeds a threshold, the state of distraction is detected

Output	Applicable?	Driver State	Notes
Driver State: Type	[X] Yes [ ] No [ ] Unknown	[ ] Visual Distraction [ ] Cognitive Distraction [X] Inattention [ ] ___ [ ] ___	
___	[ ] Yes [ ] No [ ] Unknown	[ ] ___ [ ] ___ [ ] ___ [ ] ___ [ ] ___	
___	[ ] Yes [ ] No [ ] Unknown	[ ] ___ [ ] ___ [ ] ___ [ ] ___ [ ] ___	

Manufacturer: Volvo | **Model Year:** 2008/2009/2010 S80, V70, XC70 (U.S.), 2009 XC90 (U.S.) | ☐ **Aftermarket** *or* ☒ **OEM**

System Name: Driver Alert Control | 2010 XC60 (U.S.), XC70 (U.S., N.Z.), S80 (U.S.) | ☒ **Production** *or* ☐ **Research**

☒ Standard configuration ☐ Reconfigurable Notes:

Countermeasure-Purpose

Output: Concurrent	**Applicable?**			**System Type**					**Notes**
Distraction Feedback	☒ Yes	☐ No	☐ Unknown	☐ Distraction Prevention	☒ Distraction Mitigation	☐ Collision Mitigation	☐ ____	☐ ____	
In-Vehicle Information Management	☐ Yes	☒ No	☐ Unknown	☐ Distraction Prevention	☐ Distraction Mitigation	☐ ____	☐ ____	☐ ____	
CWS Adaptation	☐ Yes	☒ No	☐ Unknown	☐ Adaptive Passive Warning	☐ Shift to Active if Distracted	☐ Adaptive Active Assistance	☐ ____	☐ ____	
Attention Redirection	☐ Yes	☒ No	☐ Unknown	☐ Forward Hazard	☐ Peripheral Hazard	☐ Speed Control	☐ ____	☐ ____	
________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
Output: Post-Drive	**Applicable?**			**System Type**					**Notes**
Behavioral Change	☐ Yes	☒ No	☐ Unknown	☐ Driver	☐ Fleet Manager	☐ ____	☐ ____	☐ ____	
________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	

Manufacturer: Volvo **Model Year:** 2008/2009/2010 S80, V70, XC70 (U.S.), 2009 XC90 (U.S.) ☐ **Aftermarket** *or* ☒ **OEM**

System Name: Driver Alert Control 2010 XC60 (U.S.), XC70 (U.S., N.Z.), S80 (U.S.) ☒ **Production** *or* ☐ **Research**

Countermeasure-Function

Output: Concurrent	Applicable?			Specification					Notes
Distraction Alert Display Timing	☒ Yes	☐ No	☐ Unknown	☒ Real Time	☐ Delayed	☐ ______	☐ ______	☐ ______	
Distraction Alert Specificity	☒ Yes	☐ No	☐ Unknown	☒ Visual Distraction	☐ Cognitive Distraction	☒ Inattention	☐ ______	☐ ______	
Attention Feedback Presentation	☒ Yes	☐ No	☐ Unknown	☒ Discrete Alert	☒ Continuous Level	☐ ______	☐ ______	☐ ______	Continuously displayed graded concentration level feedback (physically displayed as 5 bars). A binary aural and visual (coffee cup) and verbal (Time for a Break) warning is displayed if it reaches a threshold.
Distraction Alert Modality	☒ Yes	☐ No	☐ Unknown	☐ Tone	☒ Voice	☒ Visual	☐ Haptic	☐ ______	
Distraction Alert Response Timing	☐ Yes	☒ No	☐ Unknown	☐ Milliseconds	☐ Seconds	☐ ______	☐ ______	☐ ______	
Distraction Alert Resolution	☒ Yes	☐ No	☐ Unknown	☒ Binary	☒ Graded	☐ ______	☐ ______	☐ ______	
In-Vehicle Information Management	☐ Yes	☒ No	☐ Unknown	☐ Vehicle Status	☐ Audio	☐ Telecom	☐ ______	☐ ______	
CWS Adaptation	☐ Yes	☒ No	☐ Unknown	☐ Delay if Attentive	☐ Adapt Passive Alert Intensity	☐ Adapt Active Assistance Force	☐ ______	☐ ______	
Attention Redirection Modality	☐ Yes	☒ No	☐ Unknown	☐ Tone	☐ Voice	☐ Visual	☐ Haptic	☐ ______	
______________	☐ Yes	☐ No	☐ Unknown	☐ ______	☐ ______	☐ ______	☐ ______	☐ ______	Continuously displayed graded concentration level feedback (physically displayed as 5 bars). A binary aural and visual (coffee cup) and verbal (Time for a Break) warning is displayed if it reaches a threshold.
Output: Post-Drive	**Applicable?**			**Specification**					**Notes**
Cumulative Feedback	☐ Yes	☒ No	☐ Unknown	☐ Quantitative	☐ Incident Replay	☐ ______	☐ ______	☐ ______	

Manufacturer: Volvo **Model Year:** ______ ☐ **Aftermarket** *or* ☒ **OEM**

System Name: DAC Prototype ☐ **Production** *or* ☒ **Research**

☐ Standard configuration ☐ Reconfigurable Notes:

Detection - Purpose			
Input	**Applicable?**	**Requirement**	**Notes**
Road Conditions	☐ Yes ☒ No ☐ Unknown	☐ Good visibility ☐ Visible Road Markings ☐ High Speed Roads ☐ ____ ☐ ____	
Vehicle Interior	☐ Yes ☒ No ☐ Unknown	☐ Ambient Illumination ☐ Sound Level ☐ ____ ☐ ____ ☐ ____	
Vehicle State	☐ Yes ☐ No ☒ Unknown	☐ Speed ☐ Traffic Demand ☐ Imminent Collision ☐ Lane Marking ☐ ____	
Driver	☒ Yes ☐ No ☐ Unknown	☐ Head Position ☒ Glance ☐ Posture ☐ ____ ☐ ____	
____________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Transformation	**Applicable?**	**System Type**	**Notes**
Derivative System	☒ Yes ☐ No ☐ Unknown	☒ Drowsiness Fatigue ☐ CWS ☐ ____ ☐ ____ ☐ ____	
Detection Approach	☒ Yes ☐ No ☐ Unknown	☒ Visual Search ☐ Vehicle Control ☐ ____ ☐ ____ ☐ ____	
____________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Output	**Applicable?**	**Supported**	**Notes**
Driver State	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction ☐ Cognitive Distraction ☐ ____ ☐ ____ ☐ ____	
____________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	

Manufacturer: Volvo **Model Year:** ______ [ ] **Aftermarket** *or* [X] **OEM**

System Name: DAC Prototype [ ] **Production** *or* [X] **Research**

Detection - Function			
Input	**Applicable?**	**Information Streams**	**Notes**
Driver Data	[X] Yes [ ] No [ ] Unknown	[ ] Pupil [X] Eye Gaze [ ] Head Pose [ ] ____ [ ] ____	
Vehicle Data	[ ] Yes [ ] No [X] Unknown	[ ] Longitudinal Control [ ] Lateral Control [ ] CWS [ ] ____ [ ] ____	
Environmental Data	[ ] Yes [X] No [ ] Unknown	[ ] GPS Location [ ] Headlights [ ] ____ [ ] ____ [ ] ____	
Task Data	[ ] Yes [X] No [ ] Unknown	[ ] Audio Status [ ] Phone Status [ ] IVIS Status [ ] ____ [ ] ____	
______	[ ] Yes [ ] No [ ] Unknown	[ ] ____ [ ] ____ [ ] ____ [ ] ____ [ ] ____	
______	[ ] Yes [ ] No [ ] Unknown	[ ] ____ [ ] ____ [ ] ____ [ ] ____ [ ] ____	
Transformation	**General Algorithm Information**		
Algorithm	Machine Learning? [ ] Yes [ ] No [X] Unknown	*Notes:* Algorithm is based on estimation of glance frequency, single glance duration, total glance time, and total task time in the predetermined time window with reference to the base head/eye position. Combination of vehicle signals, PERCLOS, eyes on road center point, Percent Road Center, and Absolute Percent Road Center to measure driver attentiveness to road ahead.	
Output	**Applicable?**	**Driver State**	**Notes**
Driver State: Type	[X] Yes [ ] No [ ] Unknown	[X] Visual Distraction [ ] Cognitive Distraction [ ] Inattention [ ] ____ [ ] ____	
______	[ ] Yes [ ] No [ ] Unknown	[ ] ____ [ ] ____ [ ] ____ [ ] ____ [ ] ____	
______	[ ] Yes [ ] No [ ] Unknown	[ ] ____ [ ] ____ [ ] ____ [ ] ____ [ ] ____	

Manufacturer: Volvo **Model Year:** ________ ☐ **Aftermarket** *or* ☒ **OEM**

System Name: DAC Prototype ☐ **Production** *or* ☒ **Research**

☒ Standard configuration ☐ Reconfigurable Notes:

Countermeasure-Purpose

Output: Concurrent	Applicable?			System Type					Notes
Distraction Feedback	☒ Yes	☐ No	☐ Unknown	☐ Distraction Prevention	☒ Distraction Mitigation	☐ Collision Mitigation	☐ ____	☐ ____	
In-Vehicle Information Management	☐ Yes	☒ No	☐ Unknown	☐ Distraction Prevention	☐ Distraction Mitigation	☐ ____	☐ ____	☐ ____	
CWS Adaptation	☐ Yes	☒ No	☐ Unknown	☐ Adaptive Passive Warning	☐ Shift to Active if Distracted	☐ Adaptive Active Assistance	☐ ____	☐ ____	
Attention Redirection	☐ Yes	☒ No	☐ Unknown	☐ Forward Hazard	☐ Peripheral Hazard	☐ Speed Control	☐ ____	☐ ____	
________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
Output: Post-Drive	**Applicable?**			**System Type**					**Notes**
Behavioral Change	☐ Yes	☒ No	☐ Unknown	☐ Driver	☐ Fleet Manager	☐ ____	☐ ____	☐ ____	
________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	

Manufacturer: Volvo **Model Year:** ______ ☐ **Aftermarket** *or* ☒ **OEM**

System Name: DAC Prototype ☐ **Production** *or* ☒ **Research**

Countermeasure-Function

Output: Concurrent	Applicable?	Specification	Notes
Distraction Alert Display Timing	☒ Yes ☐ No ☐ Unknown	☒ Real Time ☐ Delayed ☐ ____ ☐ ____ ☐ ____	
Distraction Alert Specificity	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction ☐ Cognitive Distraction ☐ Inattention ☐ ____ ☐ ____	
Attention Feedback Presentation	☒ Yes ☐ No ☐ Unknown	☒ Discrete Alert ☒ Continuous Level ☐ ____ ☐ ____ ☐ ____	
Distraction Alert Modality	☒ Yes ☐ No ☐ Unknown	☐ Tone ☒ Voice ☒ Visual ☒ Haptic ☐ ____	
Distraction Alert Response Timing	☐ Yes ☐ No ☒ Unknown	☐ Milliseconds ☐ Seconds ☐ ____ ☐ ____ ☐ ____	
Distraction Alert Resolution	☐ Yes ☐ No ☒ Unknown	☐ Binary ☐ Graded ☐ ____ ☐ ____ ☐ ____	
In-Vehicle Information Management	☐ Yes ☒ No ☐ Unknown	☐ Vehicle Status ☐ Audio ☐ Telecom ☐ ____ ☐ ____	
CWS Adaptation	☐ Yes ☒ No ☐ Unknown	☐ Delay if Attentive ☐ Adapt Passive Alert Intensity ☐ Adapt Active Assistance Force ☐ ____ ☐ ____	
Attention Redirection Modality	☐ Yes ☒ No ☐ Unknown	☐ Tone ☐ Voice ☐ Visual ☐ Haptic ☐ ____	
____________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Output: Post-Drive	**Applicable?**	**Specification**	**Notes**
Cumulative Feedback	☐ Yes ☒ No ☐ Unknown	☐ Quantitative ☐ Incident Replay ☐ ____ ☐ ____ ☐ ____	

Manufacturer:	Saab	**Model Year:**	2008(?) 9-3 SportCombi
System Name:	AttenD		

[ ] **Aftermarket** *or* [X] **OEM**
[ ] **Production** *or* [X] **Research**

[X] Standard configuration [ ] Reconfigurable Notes:

Detection - Purpose

Input	**Applicable?**	**Requirement**	**Notes**
Road Conditions	[X] Yes [ ] No [ ] Unknown	[ ] Good visibility [ ] Visible Road Markings [X] High Speed Roads [ ] ______ [ ] ______	In an urban environment (low-speed) the driver attention zone is considered wide and the algorithm allows more head movement but a shorter time duration before the warning. In a highway environment (high-speed) the attention zone is narrower and consequently less head movement and longer time before warning would be considered
Vehicle Interior	[X] Yes [ ] No [ ] Unknown	[X] Ambient Illumination [ ] Sound Level [ ] ______ [ ] ______ [ ] ______	Glasses is OK. However, thicker lenses and frames could make the system confused
Vehicle State	[X] Yes [ ] No [ ] Unknown	[X] Speed [ ] Traffic Demand [ ] Imminent Collision [ ] ______ [ ] ______	The system is speed-sensitive and can distinguish between urban and highway driving environments.
Driver	[X] Yes [ ] No [ ] Unknown	[ ] Head Position [X] Glance [ ] Posture [ ] ______ [ ] ______	
________________	[ ] Yes [ ] No [ ] Unknown	[ ] ______ [ ] ______ [ ] ______ [ ] ______ [ ] ______	
Transformation	**Applicable?**	**System Type**	**Notes**
Derivative System	[X] Yes [ ] No [ ] Unknown	[X] Drowsiness Fatigue [ ] CWS [ ] ______ [ ] ______ [ ] ______	
Detection Approach	[X] Yes [ ] No [ ] Unknown	[X] Visual Search [ ] Vehicle Control [ ] ______ [ ] ______ [ ] ______	
Output	**Applicable?**	**Supported**	**Notes**
Driver State	[X] Yes [ ] No [ ] Unknown	[X] Visual Distraction [ ] Cognitive Distraction [X] Inattentive [ ] ______ [ ] ______	
________________	[ ] Yes [ ] No [ ] Unknown	[ ] ______ [ ] ______ [ ] ______ [ ] ______ [ ] ______	

Manufacturer: Saab **Model Year:** 2008(?) 9-3 SportCombi ☐ **Aftermarket** *or* ☒ **OEM**

System Name: AttenD ☐ **Production** *or* ☒ **Research**

Detection - Function

Input	Applicable?	Information Streams	Notes
Driver Data	☒ Yes ☐ No ☐ Unknown	☒ Pupil ☒ Eye Gaze ☐ Head Pose ☐ ___ ☐ ___	
Vehicle Data	☐ Yes ☒ No ☐ Unknown	☐ Longitudinal Control ☐ Lateral Control ☐ CWS ☐ ___ ☐ ___	
Environmental Data	☒ Yes ☐ No ☐ Unknown	☒ GPS Location ☐ Headlights ☒ Type of Road ☐ ___ ☐ ___	Type of road: urban, highway, etc.
Task Data	☐ Yes ☒ No ☐ Unknown	☐ Audio Status ☐ Phone Status ☐ IVIS Status ☐ ___ ☐ ___	
___	☐ Yes ☐ No ☐ Unknown	☐ ___ ☐ ___ ☐ ___ ☐ ___ ☐ ___	
___	☐ Yes ☐ No ☐ Unknown	☐ ___ ☐ ___ ☐ ___ ☐ ___ ☐ ___	
Transformation	**General Algorithm Information**		
Algorithm	Machine Learning? ☐ Yes ☐ No ☒ Unknown	*Notes:* There are two types of algorithms for visual distraction and drowsiness detection	
Output	**Applicable?**	**Driver State**	**Notes**
Driver State: Type	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction ☐ Cognitive Distraction ☒ Inattention ☐ ___ ☐ ___	
___	☐ Yes ☐ No ☐ Unknown	☐ ___ ☐ ___ ☐ ___ ☐ ___ ☐ ___	
___	☐ Yes ☐ No ☐ Unknown	☐ ___ ☐ ___ ☐ ___ ☐ ___ ☐ ___	

Manufacturer: Saab **Model Year:** 2008(?) 9-3 SportCombi [ ] **Aftermarket** *or* [X] **OEM**

System Name: AttenD [ ] **Production** *or* [X] **Research**

[X] Standard configuration [ ] Reconfigurable Notes:

Countermeasure-Purpose

Output: Concurrent	Applicable?			System Type					Notes
Distraction Feedback	[X] Yes	[ ] No	[ ] Unknown	[ ] Distraction Prevention	[X] Distraction Mitigation	[ ] Collision Mitigation	[ ] _____	[ ] _____	
In-Vehicle Information Management	[ ] Yes	[X] No	[ ] Unknown	[ ] Distraction Prevention	[ ] Distraction Mitigation	[ ] _____	[ ] _____	[ ] _____	
CWS Adaptation	[ ] Yes	[X] No	[ ] Unknown	[ ] Adaptive Passive Warning	[ ] Shift to Active if Distracted	[ ] Adaptive Active Assistance	[ ] _____	[ ] _____	
Attention Redirection	[ ] Yes	[X] No	[ ] Unknown	[ ] Forward Hazard	[ ] Peripheral Hazard	[ ] Speed Control	[ ] _____	[ ] _____	
_______________	[ ] Yes	[ ] No	[ ] Unknown	[ ] _____	[ ] _____	[ ] _____	[ ] _____	[ ] _____	
_______________	[ ] Yes	[ ] No	[ ] Unknown	[ ] _____	[ ] _____	[ ] _____	[ ] _____	[ ] _____	
Output: Post-Drive	**Applicable?**			**System Type**					**Notes**
Behavioral Change	[ ] Yes	[X] No	[ ] Unknown	[ ] Driver	[ ] Fleet Manager	[ ] _____	[ ] _____	[ ] _____	
_______________	[ ] Yes	[ ] No	[ ] Unknown	[ ] _____	[ ] _____	[ ] _____	[ ] _____	[ ] _____	
_______________	[ ] Yes	[ ] No	[ ] Unknown	[ ] _____	[ ] _____	[ ] _____	[ ] _____	[ ] _____	
_______________	[ ] Yes	[ ] No	[ ] Unknown	[ ] _____	[ ] _____	[ ] _____	[ ] _____	[ ] _____	

Manufacturer: Saab **Model Year:** 2008(?) 9-3 SportCombi ☐ **Aftermarket** *or* ☒ **OEM**

System Name: AttenD ☐ **Production** *or* ☒ **Research**

Output: Concurrent	Applicable?	Specification	Notes
Distraction Alert Display Timing	☒ Yes ☐ No ☐ Unknown	☒ Real Time ☐ Delayed ☐ ☐ ☐	
Distraction Alert Specificity	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction ☐ Cognitive Distraction ☒ Inattention ☐ ☐	drowsiness detection
Attention Feedback Presentation	☒ Yes ☐ No ☐ Unknown	☒ Discrete Alert ☐ Continuous Level ☐ ☐ ☐	
Distraction Alert Modality	☒ Yes ☐ No ☐ Unknown	☒ Tone ☒ Voice ☒ Visual ☒ Haptic ☐	Haptic mode is for visual distraction warning. Audible and textual warnings would inform driver about three levels of drowsiness: slightly drowsy, drowsy and very drowsy. The warning can be cancelled by pressing a reset button that will cause the system re-activation.
Distraction Alert Response Timing	☒ Yes ☐ No ☐ Unknown	☐ Milliseconds ☐ Seconds ☐ ☐ ☐	unknown
Distraction Alert Resolution	☒ Yes ☐ No ☐ Unknown	☒ Binary ☒ Graded ☐ ☐ ☐	Binary for distraction and graded for drowsiness
In-Vehicle Information Management	☐ Yes ☒ No ☐ Unknown	☐ Vehicle Status ☐ Audio ☐ Telecom ☐ ☐	
CWS Adaptation	☐ Yes ☒ No ☐ Unknown	☐ Delay if Attentive ☐ Adapt Passive Alert Intensity ☐ Adapt Active Assistance Force ☐ ☐	
Attention Redirection Modality	☐ Yes ☒ No ☐ Unknown	☐ Tone ☐ Voice ☐ Visual ☐ Haptic ☐	
________________	☐ Yes ☐ No ☐ Unknown	☐ ☐ ☐ ☐ ☐	
Output: Post-Drive	**Applicable?**	**Specification**	**Notes**
Cumulative Feedback	☐ Yes ☒ No ☐ Unknown	☐ Quantitative ☐ Incident Replay ☐ ☐ ☐	

Manufacturer: Saab

System Name: ComSense

Model Year: 2006/2007/2008/2009 9-5 Sedan and SportCombi range (EU/UK); 2008/2009 9-3 Sport Sedan/SportCombi/Convertible (UK/EU, AU)

☐ **Aftermarket** *or* ☒ **OEM**

☒ **Production** *or* ☐ **Research**

☒ Standard configuration ☐ Reconfigurable Notes:

Detection - Purpose

Input	Applicable?	Requirement	Notes
Road Conditions	☐ Yes ☐ No ☒ Unknown	☐ Good visibility ☐ Visible Road Markings ☐ High Speed Roads ☐ ____ ☐ ____	
Vehicle Interior	☐ Yes ☒ No ☐ Unknown	☐ Ambient Illumination ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Vehicle State	☒ Yes ☐ No ☐ Unknown	☐ Speed ☐ Traffic Demand ☐ Imminent Collision ☒ Maneuver Performance ☐ ____	System uses as an input the brakes or turn indicators. It detects if the driver performs a maneuver such as lane changing, passing, or turning.
Driver	☐ Yes ☒ No ☐ Unknown	☐ Head Position ☐ Glance ☐ Posture ☐ ____ ☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Transformation	**Applicable?**	**System Type**	**Notes**
Derivative System	☒ Yes ☐ No ☐ Unknown	☐ Drowsiness Fatigue ☐ CWS ☒ Workload Manager ☐ Distraction ☐ ____	
Detection Approach	☒ Yes ☐ No ☐ Unknown	☐ Visual Search ☒ Vehicle Control ☒ Task Demand ☐ Driving Environment ☐ ____	Task demands are detected through the vehicle control sensors: brake and steering wheel positions
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Output	**Applicable?**	**Supported**	**Notes**
Driver State	☒ Yes ☐ No ☐ Unknown	☐ Visual Distraction ☐ Cognitive Distraction ☒ High Workload ☐ Inattention ☐ ____	The workload is considered high when a driver performs specific maneuvers, e.g., lane change, passing, or turning, and uses in-vehicle devices
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	

Manufacturer: Saab
System Name: ComSense

Model Year: 2006/2007/2008/2009 9-5 Sedan and SportCombi range (EU/UK); 2008/2009 9-3 Sport Sedan/SportCombi/Convertible (UK/EU, AU)

[ ] **Aftermarket** *or* [X] **OEM**
[X] **Production** *or* [ ] **Research**

Detection - Function									
Input	**Applicable?**			**Information Streams**					**Notes**
Driver Data	[ ] Yes	[X] No	[ ] Unknown	[ ] Pupil	[ ] Eye Gaze	[ ] Head Pose	[ ] ____	[ ] ____	
Vehicle Data	[X] Yes	[ ] No	[ ] Unknown	[X] Longitudinal Control	[X] Lateral Control	[ ] CWS	[ ] ____	[ ] ____	
Environmental Data	[X] Yes	[ ] No	[ ] Unknown	[ ] GPS Location	[X] Headlights	[X] Wiper	[ ] ____	[ ] ____	Environmental sensors for external light sensor /headlamp status, wiper status, etc (NOT SURE ABOUT THIS!)
Task Data	[X] Yes	[ ] No	[ ] Unknown	[ ] Audio Status	[X] Phone Status	[X] In-vehicle Device Status	[ ] ____	[ ] ____	
________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] ____	
________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] ____	
Transformation	**General Algorithm Information**								
Algorithm	Machine Learning? [ ] Yes	[ ] No	[X] Unknown	*Notes:*					
Output	**Applicable?**			**Driver State**					**Notes**
Driver State: Type	[X] Yes	[ ] No	[ ] Unknown	[ ] Visual Distraction	[ ] Cognitive Distraction	[ ] Inattention	[X] High Workload	[ ] ____	
________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] ____	
________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] ____	

Manufacturer: Saab **Model Year:** 2006/2007/2008/2009 9-5 Sedan and SportCombi range (EU/UK); 2008/2009 9-3 Sport Sedan/SportCombi/Convertible (UK/EU, AU)

System Name: ComSense

☐ **Aftermarket** *or* ☒ **OEM**

☒ **Production** *or* ☐ **Research**

☒ Standard configuration ☐ Reconfigurable Notes:

Countermeasure-Purpose									
Output: Concurrent	**Applicable?**			**System Type**					**Notes**
Distraction Feedback	☒ Yes	☐ No	☐ Unknown	☒ Distraction Prevention	☐ Distraction Mitigation	☐ Collision Mitigation	☐ ______	☐ ______	
In-Vehicle Information Management	☒ Yes	☐ No	☐ Unknown	☒ Distraction Prevention	☐ Distraction Mitigation	☐ ______	☐ ______	☐ ______	
CWS Adaptation	☐ Yes	☒ No	☐ Unknown	☐ Adaptive Passive Warning	☐ Shift to Active if Distracted	☐ Adaptive Active Assistance	☐ ______	☐ ______	
Attention Redirection	☐ Yes	☒ No	☐ Unknown	☐ Forward Hazard	☐ Peripheral Hazard	☐ Speed Control	☐ Task Relevant	☐ ______	
________________	☐ Yes	☐ No	☐ Unknown	☐ ______	☐ ______	☐ ______	☐ ______	☐ ______	
________________	☐ Yes	☐ No	☐ Unknown	☐ ______	☐ ______	☐ ______	☐ ______	☐ ______	
Output: Post-Drive	**Applicable?**			**System Type**					**Notes**
Behavioral Change	☐ Yes	☒ No	☐ Unknown	☐ Driver	☐ Fleet Manager	☐ ______	☐ ______	☐ ______	
________________	☐ Yes	☐ No	☐ Unknown	☐ ______	☐ ______	☐ ______	☐ ______	☐ ______	
________________	☐ Yes	☐ No	☐ Unknown	☐ ______	☐ ______	☐ ______	☐ ______	☐ ______	
________________	☐ Yes	☐ No	☐ Unknown	☐ ______	☐ ______	☐ ______	☐ ______	☐ ______	

Manufacturer: Saab | **Model Year:** 2006/2007/2008/2009 9-5 Sedan and SportCombi range (EU/UK); 2008/2009 9-3 Sport Sedan/SportCombi/Convertible (UK/EU, AU) | ☐ **Aftermarket** *or* ☒ **OEM**

System Name: ComSense | ☒ **Production** *or* ☐ **Research**

Countermeasure-Function

Output: Concurrent	Applicable?			Specification					Notes
Distraction Alert Display Timing	☐ Yes	☒ No	☐ Unknown	☐ Real Time	☐ Delayed	☐ ____	☐ ____	☐ ____	
Distraction Alert Specificity	☒ Yes	☐ No	☐ Unknown	☐ Visual Distraction	☐ Cognitive Distraction	☐ Inattention	☒ Workload	☐ ____	
Attention Feedback Presentation	☐ Yes	☒ No	☐ Unknown	☐ Discrete Alert	☐ Continuous Level	☐ ____	☐ ____	☐ ____	
Distraction Alert Modality	☐ Yes	☒ No	☐ Unknown	☐ Tone	☐ Voice	☐ Visual	☐ Haptic	☐ ____	
Distraction Alert Response Timing	☐ Yes	☒ No	☐ Unknown	☐ Milliseconds	☐ Seconds	☐ ____	☐ ____	☐ ____	
Distraction Alert Resolution	☒ Yes	☐ No	☐ Unknown	☒ Binary	☐ Graded	☐ ____	☐ ____	☐ ____	
In-Vehicle Information Management	☒ Yes	☐ No	☐ Unknown	☐ Vehicle Status	☐ Audio	☒ Telecom	☐ ____	☐ ____	
CWS Adaptation	☐ Yes	☒ No	☐ Unknown	☐ Delay if Attentive	☐ Adapt Passive Alert Intensity	☐ Adapt Active Assistance Force	☐ ____	☐ ____	
Attention Redirection Modality	☐ Yes	☒ No	☐ Unknown	☐ Tone	☐ Voice	☐ Visual	☐ Haptic	☐ ____	
____________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
Output: Post-Drive	**Applicable?**			**Specification**					**Notes**
Cumulative Feedback	☐ Yes	☒ No	☐ Unknown	☐ Quantitative	☐ Incident Replay	☐ ____	☐ ____	☐ ____	

Manufacturer: Lexus | **Model Year:** Asia, U.S., EU; not confirmed for specific models/years | [ ] **Aftermarket** *or* [X] **OEM**

System Name: Driver Monitoring System | 2008/2009/2010 LS 460, LS 600h, 2010 LS 600h L, HS 250 | [X] **Production** *or* [ ] **Research**

[X] Standard configuration [ ] Reconfigurable Notes:

Detection - Purpose

Input	Applicable?	Requirement	Notes
Road Conditions	[ ] Yes [ ] No [X] Unknown	[ ] Good visibility [ ] Visible Road Markings [ ] High Speed Roads [ ] ____ [ ] ____	
Vehicle Interior	[ ] Yes [X] No [ ] Unknown	[ ] Ambient Illumination [ ] Sound Level [ ] ____ [ ] ____ [ ] ____	The system works under different illumination conditions. The system works to certain degree with sunglasses
Vehicle State	[X] Yes [ ] No [ ] Unknown	[ ] Speed [ ] Traffic Demand [X] Imminent Collision [ ] ____ [ ] ____	The DMS system is a part of the advanced Pre-Crash Safety (PCS) system that detects obstacles or moving objects ahead.
Driver	[X] Yes [ ] No [ ] Unknown	[X] Head Position [X] Glance [ ] Posture [ ] ____ [ ] ____	
____________	[ ] Yes [ ] No [ ] Unknown	[ ] ____ [ ] ____ [ ] ____ [ ] ____ [ ] ____	
Transformation	**Applicable?**	**System Type**	**Notes**
Derivative System	[X] Yes [ ] No [ ] Unknown	[ ] Drowsiness Fatigue [X] CWS [ ] ____ [ ] ____ [ ] ____	The DMS system is a part of the advanced Pre-Crash Safety (PCS) system that detects obstacles or moving objects ahead.
Detection Approach	[X] Yes [ ] No [ ] Unknown	[X] Visual Search [ ] Vehicle Control [ ] ____ [ ] ____ [ ] ____	
____________	[ ] Yes [ ] No [ ] Unknown	[ ] ____ [ ] ____ [ ] ____ [ ] ____ [ ] ____	
Output	**Applicable?**	**Supported**	**Notes**
Driver State	[X] Yes [ ] No [ ] Unknown	[X] Visual Distraction [ ] Cognitive Distraction [X] Drowsiness [ ] ____ [ ] ____	
____________	[ ] Yes [ ] No [ ] Unknown	[ ] ____ [ ] ____ [ ] ____ [ ] ____ [ ] ____	

Manufacturer: Lexus
System Name: Driver Monitoring System
Model Year: Asia, U.S., EU; not confirmed for specific models/years
2008/2009/2010 LS 460, LS 600h, 2010 LS 600h L, HS 250

☐ **Aftermarket** *or* ☒ **OEM**
☒ **Production** *or* ☐ **Research**

Detection - Function			
Input	**Applicable?**	**Information Streams**	**Notes**
Driver Data	☒ Yes ☐ No ☐ Unknown	☒ Pupil ☒ Eye Gaze ☒ Head Pose ☐ ☐	
Vehicle Data	☒ Yes ☐ No ☐ Unknown	☐ Longitudinal Control ☐ Lateral Control ☒ CWS ☐ ☐	
Environmental Data	☐ Yes ☒ No ☐ Unknown	☐ GPS Location ☐ Headlights ☐ ☐ ☐	
Task Data	☐ Yes ☐ No ☐ Unknown	☐ Audio Status ☐ Phone Status ☐ ☐ ☐	
________	☐ Yes ☐ No ☐ Unknown	☐ ☐ ☐ ☐ ☐	
________	☐ Yes ☐ No ☐ Unknown	☐ ☐ ☐ ☐ ☐	

Transformation	**General Algorithm Information**
Algorithm	Machine Learning? ☐ Yes ☐ No ☒ Unknown — *Notes:* The algorithm is based on a driver's facial features and head position in order to assess if the driver is inattentive due to distraction or fatigue. The system detects distraction if the driver's head is turned away from the road at an angle of more than 15 degrees.

Output	**Applicable?**	**Driver State**	**Notes**
Driver State: Type	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction ☐ Cognitive Distraction ☒ Inattention ☐ ☐	Inattention: fatigue or drowsiness
________	☐ Yes ☐ No ☐ Unknown	☐ ☐ ☐ ☐ ☐	
________	☐ Yes ☐ No ☐ Unknown	☐ ☐ ☐ ☐ ☐	

Manufacturer: Lexus **Model Year:** Asia, U.S., EU; not confirmed for specific models/years ☐ **Aftermarket** *or* ☒ **OEM**

System Name: Driver Monitoring System 2008/2009/2010 LS 460, LS 600h, 2010 LS 600h L, HS 250 ☒ **Production** *or* ☐ **Research**

☒ Standard configuration ☐ Reconfigurable Notes:

Countermeasure-Purpose

Output: Concurrent	**Applicable?**	**System Type**	**Notes**
Distraction Feedback	☒ Yes ☐ No ☐ Unknown	☐ Distraction Prevention ☒ Distraction Mitigation ☒ Collision Mitigation ☐ ______ ☐ ______	The system automatically activates the Pre-Crash warning buzzer and briefly applies the brakes to warn of the danger. If this still fails to prompt action from the driver, the PCS engages emergency braking preparation and pre-tensioning of the front seatbelts.
In-Vehicle Information Management	☐ Yes ☒ No ☐ Unknown	☐ Distraction Prevention ☐ Distraction Mitigation ☐ ______ ☐ ______ ☐ ______	
CWS Adaptation	☒ Yes ☐ No ☐ Unknown	☐ Adaptive Passive Warning ☒ Shift to Active if Distracted ☐ Adaptive Active Assistance ☐ ______ ☐ ______	
Attention Redirection	☒ Yes ☐ No ☐ Unknown	☒ Forward Hazard ☐ Peripheral Hazard ☐ Speed Control ☐ ______ ☐ ______	Could be peripheral hazard as well
______________	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ ______	
______________	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ ______	

Output: Post-Drive	**Applicable?**	**System Type**	**Notes**
Behavioral Change	☐ Yes ☒ No ☐ Unknown	☐ Driver ☐ Fleet Manager ☐ ______ ☐ ______ ☐ ______	
______________	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ ______	
______________	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ ______	
______________	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ ______	

Manufacturer: Lexus **Model Year:** Asia, U.S., EU; not confirmed for specific models/years [ ] **Aftermarket** *or* [X] **OEM**

System Name: Driver Monitoring System 2008/2009/2010 LS 460, LS 600h, 2010 LS 600h L, HS 250 [X] **Production** *or* [ ] **Research**

Countermeasure-Function									
Output: Concurrent	**Applicable?**			**Specification**					**Notes**
Distraction Alert Display Timing	[X] Yes	[ ] No	[ ] Unknown	[X] Real Time	[ ] Delayed	[ ] _____	[ ] _____	[ ] _____	
Distraction Alert Specificity	[X] Yes	[ ] No	[ ] Unknown	[X] Visual Distraction	[ ] Cognitive Distraction	[X] Inattention	[ ] _____	[ ] _____	Inattention: fatigue or drowsiness
Attention Feedback Presentation	[X] Yes	[ ] No	[ ] Unknown	[X] Discrete Alert	[ ] Continuous Level	[ ] _____	[ ] _____	[ ] _____	
Distraction Alert Modality	[X] Yes	[ ] No	[ ] Unknown	[X] Tone	[ ] Voice	[ ] Visual	[X] Haptic	[X] Brake	
Distraction Alert Response Timing	[X] Yes	[ ] No	[ ] Unknown	[ ] Milliseconds	[ ] Seconds	[ ] _____	[ ] _____	[ ] _____	Not specified
Distraction Alert Resolution	[X] Yes	[ ] No	[ ] Unknown	[ ] Binary	[X] Graded	[ ] _____	[ ] _____	[ ] _____	System alerts when there is a obstacle ahead and driver is considered distracted. The system alert the driver if there is no response from the driver, it will automatically activate pre-crash warnings and apply the brakes, as necessary
In-Vehicle Information Management	[ ] Yes	[X] No	[ ] Unknown	[ ] Vehicle Status	[ ] Audio	[ ] Telecom	[ ] _____	[ ] _____	
CWS Adaptation	[X] Yes	[ ] No	[ ] Unknown	[ ] Delay if Attentive	[ ] Adapt Passive Alert Intensity	[X] Adapt Active Assistance Force	[ ] _____	[ ] _____	Emergency braking preparation and pre-tensioning of the front seatbelts
Attention Redirection Modality	[ ] Yes	[X] No	[ ] Unknown	[ ] Tone	[ ] Voice	[ ] Visual	[ ] Haptic	[ ] _____	
_______________	[ ] Yes	[ ] No	[ ] Unknown	[ ] _____	[ ] _____	[ ] _____	[ ] _____	[ ] _____	
Output: Post-Drive	**Applicable?**			**Specification**					**Notes**
Cumulative Feedback	[ ] Yes	[X] No	[ ] Unknown	[ ] Quantitative	[ ] Incident Replay	[ ] _____	[ ] _____	[ ] _____	

Manufacturer: Delphi **Model Year:** ______ [ ] **Aftermarket** *or* [X] **OEM**

System Name: SAVE-IT System [ ] **Production** *or* [X] **Research**

[X] Standard configuration [ ] Reconfigurable Notes:

Detection - Purpose

Input	**Applicable?**	**Requirement**	**Notes**
Road Conditions	[ ] Yes [ ] No [X] Unknown	[ ] Good visibility [ ] Visible Road Markings [ ] High Speed Roads [ ] ______ [ ] ______	
Vehicle Interior	[ ] Yes [ ] No [X] Unknown	[ ] Ambient Illumination [ ] Sound Level [ ] ______ [ ] ______ [ ] ______	
Vehicle State	[ ] Yes [ ] No [X] Unknown	[ ] Speed [ ] Traffic Demand [ ] Imminent Collision [ ] ______ [ ] ______	
Driver	[X] Yes [ ] No [ ] Unknown	[X] Head Position [ ] Glance [ ] Posture [ ] ______ [ ] ______	
______________	[ ] Yes [ ] No [ ] Unknown	[ ] ______ [ ] ______ [ ] ______ [ ] ______ [ ] ______	
Transformation	**Applicable?**	**System Type**	**Notes**
Derivative System	[X] Yes [ ] No [ ] Unknown	[ ] Drowsiness Fatigue [X] CWS [ ] Distraction [ ] ______ [ ] ______	
Detection Approach	[X] Yes [ ] No [ ] Unknown	[X] Visual Search [ ] Vehicle Control [ ] ______ [ ] ______ [ ] ______	
______________	[ ] Yes [ ] No [ ] Unknown	[ ] ______ [ ] ______ [ ] ______ [ ] ______ [ ] ______	
Output	**Applicable?**	**Supported**	**Notes**
Driver State	[X] Yes [ ] No [ ] Unknown	[X] Visual Distraction [ ] Cognitive Distraction [ ] ______ [ ] ______ [ ] ______	
______________	[ ] Yes [ ] No [ ] Unknown	[ ] ______ [ ] ______ [ ] ______ [ ] ______ [ ] ______	

Manufacturer: Delphi **Model Year:** ______

System Name: SAVE-IT System

☐ Aftermarket *or* ☒ OEM

☐ Production *or* ☒ Research

Detection - Function			
Input	**Applicable?**	**Information Streams**	**Notes**
Driver Data	☒ Yes ☐ No ☐ Unknown	☐ Pupil ☐ Eye Gaze ☒ Head Pose ☐ ____ ☐ ____	
Vehicle Data	☒ Yes ☐ No ☐ Unknown	☒ Longitudinal Control ☐ Lateral Control ☒ CWS ☐ ____ ☐ ____	
Environmental Data	☒ Yes ☐ No ☐ Unknown	☐ GPS Location ☐ Headlights ☒ Wipers ☐ ____ ☐ ____	
Task Data	☒ Yes ☐ No ☐ Unknown	☐ Audio Status ☐ Phone Status ☐ ____ ☐ ____ ☐ ____	Driving task demand is determined based on radar information, yaw, path, wipers, etc.
______________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
______________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Transformation	**General Algorithm Information**		
Algorithm	Machine Learning? ☐ Yes ☒ No ☐ Unknown	*Notes:*	
Output	**Applicable?**	**Driver State**	**Notes**
Driver State: Type	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction ☐ Cognitive Distraction ☐ Inattention ☐ ____ ☐ ____	
______________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
______________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	

Manufacturer: Delphi **Model Year:** ______ [ ] **Aftermarket** *or* [X] **OEM**

System Name: SAVE-IT System [ ] **Production** *or* [X] **Research**

[X] Standard configuration [ ] Reconfigurable Notes:

Countermeasure-Purpose

Output: Concurrent	**Applicable?**			**System Type**					**Notes**
Distraction Feedback	[X] Yes	[ ] No	[ ] Unknown	[X] Distraction Prevention	[X] Distraction Mitigation	[ ] Collision Mitigation	[ ] ____	[ ] ____	
In-Vehicle Information Management	[X] Yes	[ ] No	[ ] Unknown	[ ] Distraction Prevention	[X] Distraction Mitigation	[ ] ____	[ ] ____	[ ] ____	
CWS Adaptation	[ ] Yes	[X] No	[ ] Unknown	[ ] Adaptive Passive Warning	[ ] Shift to Active if Distracted	[ ] Adaptive Active Assistance	[ ] ____	[ ] ____	
Attention Redirection	[ ] Yes	[X] No	[ ] Unknown	[ ] Forward Hazard	[ ] Peripheral Hazard	[ ] Speed Control	[ ] ____	[ ] ____	
________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] ____	
________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] ____	
Output: Post-Drive	**Applicable?**			**System Type**					**Notes**
Behavioral Change	[X] Yes	[ ] No	[ ] Unknown	[X] Driver	[ ] Fleet Manager	[ ] ____	[ ] ____	[ ] ____	
________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] ____	
________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] ____	
________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] ____	

Manufacturer: Delphi **Model Year:** ______ [ ] **Aftermarket** *or* [X] **OEM**

System Name: SAVE-IT System [ ] **Production** *or* [X] **Research**

Countermeasure-Function			
Output: Concurrent	**Applicable?**	**Specification**	**Notes**
Distraction Alert Display Timing	[X] Yes [ ] No [ ] Unknown	[X] Real Time [ ] Delayed [ ] ____ [ ] ____ [ ] ____	
Distraction Alert Specificity	[X] Yes [ ] No [ ] Unknown	[X] Visual Distraction [ ] Cognitive Distraction [ ] Inattention [ ] ____ [ ] ____	
Attention Feedback Presentation	[X] Yes [ ] No [ ] Unknown	[X] Discrete Alert [ ] Continuous Level [ ] ____ [ ] ____ [ ] ____	
Distraction Alert Modality	[X] Yes [ ] No [ ] Unknown	[ ] Tone [X] Voice [X] Visual [X] Haptic [ ] ____	
Distraction Alert Response Timing	[X] Yes [ ] No [ ] Unknown	[ ] Milliseconds [ ] Seconds [ ] ____ [ ] ____ [ ] ____	Not specified
Distraction Alert Resolution	[ ] Yes [ ] No [X] Unknown	[ ] Binary [ ] Graded [ ] ____ [ ] ____ [ ] ____	
In-Vehicle Information Management	[X] Yes [ ] No [ ] Unknown	[ ] Vehicle Status [X] Audio [X] Telecom [ ] ____ [ ] ____	
CWS Adaptation	[ ] Yes [ ] No [X] Unknown	[ ] Delay if Attentive [ ] Adapt Passive Alert Intensity [ ] Adapt Active Assistance Force [ ] ____ [ ] ____	
Attention Redirection Modality	[ ] Yes [X] No [ ] Unknown	[ ] Tone [ ] Voice [ ] Visual [ ] Haptic [ ] ____	
____________	[ ] Yes [ ] No [ ] Unknown	[ ] ____ [ ] ____ [ ] ____ [ ] ____ [ ] ____	
Output: Post-Drive	**Applicable?**	**Specification**	**Notes**
Cumulative Feedback	[X] Yes [ ] No [ ] Unknown	[ ] Quantitative [ ] Incident Replay [ ] ____ [ ] ____ [ ] ____	Not specified

Manufacturer: Mercedes-Benz

System Name: Attention Assist

Model Year: (U.S., EU; not confirmed for specific models/years 2009/2010 S-Class, S63 AMG, S65 AMG; 2010 E-Class

[ ] **Aftermarket** *or* [X] **OEM**

[X] **Production** *or* [ ] **Research**

[X] Standard configuration [ ] Reconfigurable Notes:

Detection - Purpose

Input	Applicable?			Requirement					Notes
Road Conditions	[ ] Yes	[ ] No	[X] Unknown	[ ] Good visibility	[ ] Visible Road Markings	[ ] High Speed Roads	[ ] ____	[ ] ____	
Vehicle Interior	[ ] Yes	[X] No	[ ] Unknown	[ ] Ambient Illumination	[ ] Sound Level	[ ] ____	[ ] ____	[ ] ____	
Vehicle State	[X] Yes	[ ] No	[ ] Unknown	[X] Speed	[ ] Traffic Demand	[ ] Imminent Collision	[ ] ____	[ ] ____	The system is active at speeds of between 80 and 180 km/h
Driver	[ ] Yes	[X] No	[ ] Unknown	[ ] Head Position	[ ] Glance	[ ] Posture	[ ] ____	[ ] ____	
____	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] ____	

Transformation	Applicable?			System Type					Notes
Derivative System	[X] Yes	[ ] No	[ ] Unknown	[X] Drowsiness Fatigue	[ ] CWS	[ ] ____	[ ] ____	[ ] ____	
Detection Approach	[X] Yes	[ ] No	[ ] Unknown	[ ] Visual Search	[X] Vehicle Control	[ ] ____	[ ] ____	[ ] ____	
____	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] ____	

Output	Applicable?			Supported					Notes
Driver State	[X] Yes	[ ] No	[ ] Unknown	[X] Visual Distraction	[ ] Cognitive Distraction	[X] Drowsiness	[ ] ____	[ ] ____	
____	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] ____	

Manufacturer: Mercedes-Benz **Model Year:** (U.S., EU; not confirmed for specific models/years ☐ **Aftermarket** *or* ☒ **OEM**

System Name: Attention Assist 2009/2010 S-Class, S63 AMG, S65 AMG; 2010 E-Class ☒ **Production** *or* ☐ **Research**

Detection - Function			
Input	**Applicable?**	**Information Streams**	**Notes**
Driver Data	☐ Yes ☒ No ☐ Unknown	☐ Pupil ☐ Eye Gaze ☐ Head Pose ☐ ____ ☐ ____	
Vehicle Data	☒ Yes ☐ No ☐ Unknown	☒ Longitudinal Control ☒ Lateral Control ☐ CWS ☐ ____ ☐ ____	
Environmental Data	☐ Yes ☐ No ☒ Unknown	☐ GPS Location ☐ Headlights ☐ ____ ☐ ____ ☐ ____	
Task Data	☐ Yes ☒ No ☐ Unknown	☐ Audio Status ☐ Phone Status ☐ IVIS Status ☐ ____ ☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	The highly sensitive sensors monitor the driver's behavior, the current driving situation, and over 70 other parameters
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Transformation	**General Algorithm Information**		
Algorithm	Machine Learning? ☐ Yes ☐ No ☒ Unknown	*Notes:* System observes a driver's behaviors and creates a unique driver profile; continually monitors driver input in relation to this profile.	
Output	**Applicable?**	**Driver State**	**Notes**
Driver State: Type	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction ☐ Cognitive Distraction ☒ Inattention ☐ ____ ☐ ____	Inattention: drowsiness
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	

Manufacturer: Mercedes-Benz **Model Year:** (U.S., EU; not confirmed for specific models/years 2009/2010 S-Class, S63 AMG, S65 AMG; 2010 E-Class ☐ **Aftermarket** *or* ☒ **OEM**

System Name: Attention Assist ☒ **Production** *or* ☐ **Research**

☒ Standard configuration ☐ Reconfigurable Notes:

Countermeasure-Purpose									
Output: Concurrent	**Applicable?**			**System Type**					**Notes**
Distraction Feedback	☒ Yes	☐ No	☐ Unknown	☐ Distraction Prevention	☒ Distraction Mitigation	☐ Collision Mitigation	☐ _____	☐ _____	
In-Vehicle Information Management	☐ Yes	☒ No	☐ Unknown	☐ Distraction Prevention	☐ Distraction Mitigation	☐ _____	☐ _____	☐ _____	
CWS Adaptation	☐ Yes	☒ No	☐ Unknown	☐ Adaptive Passive Warning	☐ Shift to Active if Distracted	☐ Adaptive Active Assistance	☐ _____	☐ _____	
Attention Redirection	☐ Yes	☒ No	☐ Unknown	☐ Forward Hazard	☐ Peripheral Hazard	☐ Speed Control	☐ _____	☐ _____	
_______________	☐ Yes	☐ No	☐ Unknown	☐ _____	☐ _____	☐ _____	☐ _____	☐ _____	
_______________	☐ Yes	☐ No	☐ Unknown	☐ _____	☐ _____	☐ _____	☐ _____	☐ _____	
Output: Post-Drive	**Applicable?**			**System Type**					**Notes**
Behavioral Change	☐ Yes	☒ No	☐ Unknown	☐ Driver	☐ Fleet Manager	☐ _____	☐ _____	☐ _____	
_______________	☐ Yes	☐ No	☐ Unknown	☐ _____	☐ _____	☐ _____	☐ _____	☐ _____	
_______________	☐ Yes	☐ No	☐ Unknown	☐ _____	☐ _____	☐ _____	☐ _____	☐ _____	
_______________	☐ Yes	☐ No	☐ Unknown	☐ _____	☐ _____	☐ _____	☐ _____	☐ _____	

Manufacturer: Mercedes-Benz **Model Year:** (U.S., EU; not confirmed for specific models/years 2009/2010 S-Class, S63 AMG, S65 AMG; 2010 E-Class

System Name: Attention Assist

☐ **Aftermarket** *or* ☒ **OEM**

☒ **Production** *or* ☐ **Research**

Countermeasure-Function

Output: Concurrent	Applicable?	Specification	Notes
Distraction Alert Display Timing	☒ Yes ☐ No ☐ Unknown	☒ Real Time ☐ Delayed ☐ ____ ☐ ____ ☐ ____	
Distraction Alert Specificity	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction ☐ Cognitive Distraction ☒ Inattention ☐ ____ ☐ ____	Inattention: drowsiness
Attention Feedback Presentation	☒ Yes ☐ No ☐ Unknown	☒ Discrete Alert ☐ Continuous Level ☐ ____ ☐ ____ ☐ ____	
Distraction Alert Modality	☒ Yes ☐ No ☐ Unknown	☐ Tone ☒ Voice ☒ Visual ☐ Haptic ☐ ____	Audible signal and flashing up a coffee cup icon and message “Attention Assist. Break!” on the display.
Distraction Alert Response Timing	☐ Yes ☒ No ☐ Unknown	☐ Milliseconds ☐ Seconds ☐ ____ ☐ ____ ☐ ____	
Distraction Alert Resolution	☒ Yes ☐ No ☐ Unknown	☒ Binary ☐ Graded ☐ ____ ☐ ____ ☐ ____	
In-Vehicle Information Management	☐ Yes ☒ No ☐ Unknown	☐ Vehicle Status ☐ Audio ☐ Telecom ☐ ____ ☐ ____	
CWS Adaptation	☐ Yes ☒ No ☐ Unknown	☐ Delay if Attentive ☐ Adapt Passive Alert Intensity ☐ Adapt Active Assistance Force ☐ ____ ☐ ____	
Attention Redirection Modality	☒ Yes ☐ No ☐ Unknown	☐ Tone ☒ Voice ☒ Visual ☐ Haptic ☐ ____	
____________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Output: Post-Drive	**Applicable?**	**Specification**	**Notes**
Cumulative Feedback	☐ Yes ☒ No ☐ Unknown	☐ Quantitative ☐ Incident Replay ☐ ____ ☐ ____ ☐ ____	

Manufacturer: Toyota | **Model Year:** 2008 Crown (UK, Asia) | ☐ **Aftermarket** *or* ☒ **OEM**

System Name: Wakefulness Level Judging System | ☒ **Production** *or* ☐ **Research**

☒ Standard configuration ☐ Reconfigurable Notes:

Detection - Purpose

Input	Applicable?	Requirement	Notes
Road Conditions	☐ Yes ☐ No ☒ Unknown	☐ Good visibility ☐ Visible Road Markings ☐ High Speed Roads ☐ ____ ☐ ____	
Vehicle Interior	☐ Yes ☐ No ☒ Unknown	☐ Ambient Illumination ☐ Sound Level ☐ ____ ☐ ____ ☐ ____	
Vehicle State	☒ Yes ☐ No ☐ Unknown	☒ Speed ☐ Traffic Demand ☐ Imminent Collision ☐ ____ ☐ ____	The system operates when the vehicle speed is higher than a minimum operational speed threshold determined by lane departure warning electronic control units (ECU).
Driver	☒ Yes ☐ No ☐ Unknown	☒ Head Position ☐ Glance ☐ Posture ☐ ____ ☐ ____	Wakefulness level depends on the driver face positioning: forward facing associated with high wakefulness and facing down is associated with low wakefulness.
________________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Transformation	**Applicable?**	**System Type**	**Notes**
Derivative System	☒ Yes ☐ No ☐ Unknown	☒ Drowsiness Fatigue ☐ CWS ☐ ____ ☐ ____ ☐ ____	
Detection Approach	☒ Yes ☐ No ☐ Unknown	☒ Visual Search ☒ Vehicle Control ☐ ____ ☐ ____ ☐ ____	
________________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Output	**Applicable?**	**Supported**	**Notes**
Driver State	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction ☒ Cognitive Distraction ☒ Inattention ☐ ____ ☐ ____	Inattentive: drowsy
________________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	

Manufacturer: Toyota **Model Year:** 2008 Crown (UK, Asia) ☐ **Aftermarket** *or* ☒ **OEM**

System Name: Wakefulness Level Judging System ☒ **Production** *or* ☐ **Research**

Detection - Function									
Input	**Applicable?**			**Information Streams**					**Notes**
Driver Data	☒ Yes	☐ No	☐ Unknown	☐ Pupil	☐ Eye Gaze	☐ Head Pose	☒ Face Position	☐ ____	
Vehicle Data	☒ Yes	☐ No	☐ Unknown	☒ Longitudinal Control	☒ Lateral Control	☐ CWS	☐ ____	☐ ____	
Environmental Data	☐ Yes	☐ No	☒ Unknown	☐ GPS Location	☐ Headlights	☐ ____	☐ ____	☐ ____	
Task Data	☐ Yes	☒ No	☐ Unknown	☐ Audio Status	☐ Phone Status	☐ IVIS Status	☐ ____	☐ ____	
____________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
____________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
Transformation	**General Algorithm Information**								
Algorithm	Machine Learning? ☐ Yes	☐ No	☒ Unknown	*Notes:* The algorithm is based on forward-image, facing-image, vehicle speed, and steering angle					
Output	**Applicable?**			**Driver State**					**Notes**
Driver State: Type	☒ Yes	☐ No	☐ Unknown	☐ Visual Distraction	☐ Cognitive Distraction	☒ Inattention	☐ ____	☐ ____	
____________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
____________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	

Manufacturer: Toyota **Model Year:** 2008 Crown (UK, Asia) ☐ **Aftermarket** *or* ☒ **OEM**

System Name: Wakefulness Level Judging System ☒ **Production** *or* ☐ **Research**

☒ Standard configuration ☐ Reconfigurable Notes:

Countermeasure-Purpose									
Output: Concurrent	**Applicable?**			**System Type**					**Notes**
Distraction Feedback	☒ Yes	☐ No	☐ Unknown	☐ Distraction Prevention	☒ Distraction Mitigation	☐ Collision Mitigation	☐ ____	☐ ____	
In-Vehicle Information Management	☐ Yes	☒ No	☐ Unknown	☐ Distraction Prevention	☐ Distraction Mitigation	☐ ____	☐ ____	☐ ____	
CWS Adaptation	☐ Yes	☒ No	☐ Unknown	☐ Adaptive Passive Warning	☐ Shift to Active if Distracted	☐ Adaptive Active Assistance	☐ ____	☐ ____	
Attention Redirection	☐ Yes	☒ No	☐ Unknown	☐ Forward Hazard	☐ Peripheral Hazard	☐ Speed Control	☐ ____	☐ ____	
____________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
____________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
Output: Post-Drive	**Applicable?**			**System Type**					**Notes**
Behavioral Change	☐ Yes	☒ No	☐ Unknown	☐ Driver	☐ Fleet Manager	☐ ____	☐ ____	☐ ____	
____________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
____________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
____________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	

Manufacturer: Toyota **Model Year:** 2008 Crown (UK, Asia) ☐ **Aftermarket** *or* ☒ **OEM**

System Name: Wakefulness Level Judging System ☒ **Production** *or* ☐ **Research**

Countermeasure-Function			
Output: Concurrent	**Applicable?**	**Specification**	**Notes**
Distraction Alert Display Timing	☒ Yes ☐ No ☐ Unknown	☒ Real Time ☐ Delayed ☐ _____ ☐ _____ ☐ _____	
Distraction Alert Specificity	☒ Yes ☐ No ☐ Unknown	☐ Visual Distraction ☐ Cognitive Distraction ☒ Inattention ☐ _____ ☐ _____	
Attention Feedback Presentation	☒ Yes ☐ No ☐ Unknown	☒ Discrete Alert ☐ Continuous Level ☐ _____ ☐ _____ ☐ _____	
Distraction Alert Modality	☒ Yes ☐ No ☐ Unknown	☐ Tone ☒ Voice ☐ Visual ☐ Haptic ☐ _____	
Distraction Alert Response Timing	☒ Yes ☐ No ☐ Unknown	☐ Milliseconds ☐ Seconds ☐ _____ ☐ _____ ☐ _____	Not specified
Distraction Alert Resolution	☒ Yes ☐ No ☐ Unknown	☐ Binary ☒ Graded ☐ _____ ☐ _____ ☐ _____	The system raises the alarm to wake the driver
In-Vehicle Information Management	☐ Yes ☒ No ☐ Unknown	☐ Vehicle Status ☐ Audio ☐ Telecom ☐ _____ ☐ _____	
CWS Adaptation	☒ Yes ☐ No ☐ Unknown	☐ Delay if Attentive ☐ Adapt Passive Alert Intensity ☒ Adapt Active Assistance Force ☐ _____ ☐ _____	A corrective steering torque could be applied to prevent moving out of the lane; system detection appears to be adaptive
Attention Redirection Modality	☐ Yes ☒ No ☐ Unknown	☐ Tone ☐ Voice ☐ Visual ☐ Haptic ☐ _____	
_______________	☐ Yes ☐ No ☐ Unknown	☐ _____ ☐ _____ ☐ _____ ☐ _____ ☐ _____	
Output: Post-Drive	**Applicable?**	**Specification**	**Notes**
Cumulative Feedback	☐ Yes ☒ No ☐ Unknown	☐ Quantitative ☐ Incident Replay ☐ _____ ☐ _____ ☐ _____	

Manufacturer: Seeing Machines **Model Year:** NA ☒ **Aftermarket** *or* ☐ **OEM**

System Name: Driver State Sensor ☒ **Production** *or* ☐ **Research**

☐ Standard configuration ☒ Reconfigurable Notes:

Detection - Purpose									
Input	**Applicable?**			**Requirement**					**Notes**
Road Conditions	☐ Yes	☒ No	☐ Unknown	☐ Good visibility	☐ Visible Road Markings	☐ High Speed Roads	☐ _____	☐ _____	
Vehicle Interior	☐ Yes	☒ No	☐ Unknown	☐ Ambient Illumination	☐ Sound Level	☐ _____	☐ _____	☐ _____	Will work in all light conditions
Vehicle State	☐ Yes	☒ No	☐ Unknown	☐ Speed	☐ Traffic Demand	☐ Imminent Collision	☐ _____	☐ _____	
Driver	☒ Yes	☐ No	☐ Unknown	☐ Head Position	☒ Glance	☐ Posture	☐ _____	☐ _____	Will work with glasses and sunglasses
_______________	☐ Yes	☐ No	☐ Unknown	☐ _____	☐ _____	☐ _____	☐ _____	☐ _____	
Transformation	**Applicable?**			**System Type**					**Notes**
Derivative System	☒ Yes	☐ No	☐ Unknown	☒ Drowsiness Fatigue	☐ CWS	☐ _____	☐ _____	☐ _____	A fatigue and distraction detection system
Detection Approach	☒ Yes	☐ No	☐ Unknown	☒ Visual Search	☐ Vehicle Control	☐ _____	☐ _____	☐ _____	
_______________	☐ Yes	☐ No	☐ Unknown	☐ _____	☐ _____	☐ _____	☐ _____	☐ _____	
Output	**Applicable?**			**Supported**					**Notes**
Driver State	☒ Yes	☐ No	☐ Unknown	☒ Visual Distraction	☐ Cognitive Distraction	☐ _____	☐ _____	☐ _____	
_______________	☐ Yes	☐ No	☐ Unknown	☐ _____	☐ _____	☐ _____	☐ _____	☐ _____	

Manufacturer: Seeing Machines **Model Year:** NA ☒ **Aftermarket** *or* ☐ **OEM**

System Name: ☒ **Production** *or* ☐ **Research**

Detection - Function			
Input	**Applicable?**	**Information Streams**	**Notes**
Driver Data	☒ Yes ☐ No ☐ Unknown	☒ Pupil ☒ Eye Gaze ☐ Head Pose ☐ ☐	
Vehicle Data	☐ Yes ☒ No ☐ Unknown	☐ Longitudinal Control ☐ Lateral Control ☐ CWS ☐ ☐	
Environmental Data	☐ Yes ☒ No ☐ Unknown	☐ GPS Location ☐ Headlights ☐ ☐ ☐	
Task Data	☐ Yes ☒ No ☐ Unknown	☐ Audio Status ☐ Phone Status ☐ IVIS Status ☐ ☐	
	☐ Yes ☐ No ☐ Unknown	☐ ☐ ☐ ☐ ☐	
	☐ Yes ☐ No ☐ Unknown	☐ ☐ ☐ ☐ ☐	
Transformation	**General Algorithm Information**		
Algorithm	Machine Learning? ☐ Yes ☐ No ☒ Unknown	*Notes:* Image processing algorithms that measure 3D head position and orientation and eye closure level	
Output	**Applicable?**	**Driver State**	**Notes**
Driver State: Type	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction ☐ Cognitive Distraction ☒ Inattention ☐ ☐	
	☐ Yes ☐ No ☐ Unknown	☐ ☐ ☐ ☐ ☐	
	☐ Yes ☐ No ☐ Unknown	☐ ☐ ☐ ☐ ☐	

Manufacturer: Seeing Machines **Model Year:** NA [X] **Aftermarket** *or* [ ] **OEM**

System Name: [X] **Production** *or* [ ] **Research**

[ ] Standard configuration [X] Reconfigurable Notes:

Countermeasure-Purpose									
Output: Concurrent	**Applicable?**			**System Type**					**Notes**
Distraction Feedback	[X] Yes	[ ] No	[ ] Unknown	[ ] Distraction Prevention	[X] Distraction Mitigation	[ ] Collision Mitigation	[ ] ______	[ ] ______	
In-Vehicle Information Management	[ ] Yes	[X] No	[ ] Unknown	[ ] Distraction Prevention	[ ] Distraction Mitigation	[ ] ______	[ ] ______	[ ] ______	
CWS Adaptation	[ ] Yes	[X] No	[ ] Unknown	[ ] Adaptive Passive Warning	[ ] Shift to Active if Distracted	[ ] Adaptive Active Assistance	[ ] ______	[ ] ______	
Attention Redirection	[ ] Yes	[X] No	[ ] Unknown	[ ] Forward Hazard	[ ] Peripheral Hazard	[ ] Speed Control	[ ] ______	[ ] ______	
________________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ______	[ ] ______	[ ] ______	[ ] ______	[ ] ______	
________________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ______	[ ] ______	[ ] ______	[ ] ______	[ ] ______	
Output: Post-Drive	**Applicable?**			**System Type**					**Notes**
Behavioral Change	[X] Yes	[ ] No	[ ] Unknown	[ ] Driver	[X] Fleet Manager	[ ] ______	[ ] ______	[ ] ______	
________________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ______	[ ] ______	[ ] ______	[ ] ______	[ ] ______	
________________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ______	[ ] ______	[ ] ______	[ ] ______	[ ] ______	
________________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ______	[ ] ______	[ ] ______	[ ] ______	[ ] ______	

Manufacturer: Seeing Machines **Model Year:** NA [X] **Aftermarket** *or* [ ] **OEM**

System Name: [X] **Production** *or* [ ] **Research**

Countermeasure-Function				
Output: Concurrent	**Applicable?**		**Specification**	**Notes**
Distraction Alert Display Timing	[X] Yes [ ] No [ ] Unknown		[X] Real Time [ ] Delayed [ ] ____ [ ] ____ [ ] ____	
Distraction Alert Specificity	[X] Yes [ ] No [ ] Unknown		[ ] Visual Distraction [ ] Cognitive Distraction [X] Inattention [ ] ____ [ ] ____	
Attention Feedback Presentation	[X] Yes [ ] No [ ] Unknown		[X] Discrete Alert [ ] Continuous Level [ ] ____ [ ] ____ [ ] ____	
Distraction Alert Modality	[X] Yes [ ] No [ ] Unknown		[ ] Tone Voice [ ] Visual [ ] Haptic [ ] ____	
Distraction Alert Response Timing	[ ] Yes [ ] No [X] Unknown		[ ] Milliseconds [ ] Seconds [ ] ____ [ ] ____ [ ] ____	
Distraction Alert Resolution	[X] Yes [ ] No [ ] Unknown		[X] Binary [ ] Graded [ ] ____ [ ] ____ [ ] ____	
In-Vehicle Information Management	[ ] Yes [X] No [ ] Unknown		[ ] Vehicle Status [ ] Audio [ ] Telecom [ ] ____ [ ] ____	
CWS Adaptation	[ ] Yes [X] No [ ] Unknown		[ ] Delay if Attentive [ ] Adapt Passive Alert Intensity [ ] Adapt Active Assistance Force [ ] ____ [ ] ____	
Attention Redirection Modality	[ ] Yes [X] No [ ] Unknown		[ ] Tone [ ] Voice [ ] Visual [ ] Haptic [ ] ____	
____________	[ ] Yes [ ] No [ ] Unknown		[ ] ____ [ ] ____ [ ] ____ [ ] ____ [ ] ____	
Output: Post-Drive	**Applicable?**		**Specification**	**Notes**
Cumulative Feedback	[X] Yes [ ] No [ ] Unknown		[ ] Quantitative [ ] Incident Replay [ ] ____ [ ] ____ [ ] ____	Not specified

Manufacturer: Augmented Cognition **Model Year:** NA ☐ **Aftermarket** *or* ☐ **OEM**

System Name: De-cluttering Concept Source: Fuchs et. al. cites Barker, 2004 ☐ **Production** *or* ☒ **Research**

☒ Standard configuration ☐ Reconfigurable Notes: De-cluttering mitigation (e.g. fog layer) to unclutter IVIS preventing driver distraction.

Detection - Purpose

Input	**Applicable?**			**Requirement**					**Notes**
Road Conditions	☐ Yes	☒ No	☐ Unknown	☐ Good visibility	☐ Visible Road Markings	☐ High Speed Roads	☐ _____	☐ _____	
Vehicle Interior	☒ Yes	☐ No	☐ Unknown	☐ Ambient Illumination	☐ Sound Level	☐ _____	☐ _____	☒ IVIS Status	
Vehicle State	☒ Yes	☐ No	☐ Unknown	☐ Speed	☒ Traffic Demand	☐ Imminent Collision	☐ _____	☐ _____	Aug cog mitigations are required for high stress, high demand situations (e.g., Fuchs et al., 2007). Imminent does not mean unavoidable here (unlike CIB).
Driver	☒ Yes	☐ No	☐ Unknown	☐ Head Position	☐ Glance	☐ Posture	☒ stress	☒ workload	
_____	☐ Yes	☐ No	☐ Unknown	☐ _____	☐ _____	☐ _____	☐ _____	☐ _____	
Transformation	**Applicable?**			**System Type**					**Notes**
Derivative System	☐ Yes	☒ No	☐ Unknown	☐ Drowsiness Fatigue	☐ CWS	☐ _____	☐ _____	☐ _____	
Detection Approach	☒ Yes	☐ No	☐ Unknown	☐ Visual Search	☐ Vehicle Control	☐ _____	☐ _____	☐ _____	
_____	☐ Yes	☐ No	☐ Unknown	☐ _____	☐ _____	☐ _____	☐ _____	☐ _____	
Output	**Applicable?**			**Supported**					**Notes**
Driver State	☐ Yes	☒ No	☐ Unknown	☐ Visual Distraction	☐ Cognitive Distraction	☐ _____	☐ _____	☐ _____	
_____	☐ Yes	☐ No	☐ Unknown	☐ _____	☐ _____	☐ _____	☐ _____	☐ _____	

Manufacturer: Augmented Cognition **Model Year:** NA [ ] **Aftermarket** *or* [ ] **OEM**

System Name: De-cluttering Concept Source: Fuchs et. al. cites Barker, 2004 [ ] **Production** *or* [X] **Research**

Detection - Function									
Input	**Applicable?**			**Information Streams**					**Notes**
Driver Data	[X] Yes	[ ] No	[ ] Unknown	[ ] Pupil	[ ] Eye Gaze	[ ] Head Pose	[ ] ____	[ ] __	
Vehicle Data	[X] Yes	[ ] No	[ ] Unknown	[ ] Longitudinal Control	[ ] Lateral Control	[ ] CWS	[ ] ____	[ ] __	
Environmental Data	[X] Yes	[ ] No	[ ] Unknown	[ ] GPS Location	[ ] Headlights	[ ] ____	[ ] ____	[ ] __	
Task Data	[X] Yes	[ ] No	[ ] Unknown	[ ] Audio Status	[ ] Phone Status	[X] IVIS Status	[ ] ____	[ ] __	
____________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] __	
____________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] __	
Transformation	**General Algorithm Information**								
Algorithm	Machine Learning? [X] Yes	[ ] No	[ ] Unknown	*Notes:*					
Output	**Applicable?**			**Driver State**					**Notes**
Driver State: Type	[X] Yes	[ ] No	[ ] Unknown	[ ] Visual Distraction	[ ] Cognitive Distraction	[ ] Inattention	[X] stress	[X] work	The mitigation could work better if driver state were system-specific
____________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] __	
____________	[ ] Yes	[ ] No	[ ] Unknown	[ ] ____	[ ] ____	[ ] ____	[ ] ____	[ ] __	

Manufacturer: Augmented Cognition **Model Year:** NA ☐ **Aftermarket** *or* ☐ **OEM**

System Name: De-cluttering Concept Source: Fuchs et. al. cites Barker, 2004 ☐ **Production** *or* ☒ **Research**

☐ Standard configuration ☐ Reconfigurable Notes:

Countermeasure-Purpose			
Output: Concurrent	**Applicable?**	**System Type**	**Notes**
Distraction Feedback	☐ Yes ☒ No ☐ Unknown	☐ Distraction Prevention ☐ Distraction Mitigation ☐ Collision Mitigation ☐ _____ ☐ __	
In-Vehicle Information Management	☒ Yes ☐ No ☐ Unknown	☒ Distraction Prevention ☐ Distraction Mitigation ☐ _____ ☐ _____ ☐ __	
CWS Adaptation	☐ Yes ☒ No ☐ Unknown	☐ Adaptive Passive Warning ☐ Shift to Active if Distracted ☐ Adaptive Active Assistance ☐ _____ ☐ __	
Attention Redirection	☐ Yes ☒ No ☐ Unknown	☐ Forward Hazard ☐ Peripheral Hazard ☐ Speed Control ☐ _____ ☐ __	
________________	☐ Yes ☐ No ☐ Unknown	☐ _____ ☐ _____ ☐ _____ ☐ _____ ☐ __	
________________	☐ Yes ☐ No ☐ Unknown	☐ _____ ☐ _____ ☐ _____ ☐ _____ ☐ __	
Output: Post-Drive	**Applicable?**	**System Type**	**Notes**
Behavioral Change	☐ Yes ☒ No ☐ Unknown	☐ Driver ☐ Fleet Manager ☐ _____ ☐ _____ ☐ __	
________________	☐ Yes ☐ No ☐ Unknown	☐ _____ ☐ _____ ☐ _____ ☐ _____ ☐ __	
________________	☐ Yes ☐ No ☐ Unknown	☐ _____ ☐ _____ ☐ _____ ☐ _____ ☐ __	
________________	☐ Yes ☐ No ☐ Unknown	☐ _____ ☐ _____ ☐ _____ ☐ _____ ☐ __	

Manufacturer: Augmented Cognition | **Model Year:** NA | ☐ **Aftermarket** *or* ☐ **OEM**

System Name: De-cluttering Concept | Source: Fuchs et. al. cites Barker, 2004 | ☐ **Production** *or* ☒ **Research**

☒ Standard configuration ☐ Reconfigurable Notes: Earcons provide aural feedback for IVIS actions

Detection - Purpose

Input	Applicable?	Requirement	Notes
Road Conditions	☐ Yes ☒ No ☐ Unknown	☐ Good visibility ☐ Visible Road Markings ☐ High Speed Roads ☐ ______ ☐ ______	
Vehicle Interior	☒ Yes ☐ No ☐ Unknown	☐ Ambient Illumination ☐ Sound Level ☐ ______ ☐ ______ ☒ IVIS Status	
Vehicle State	☒ Yes ☐ No ☐ Unknown	☒ Speed ☒ Traffic Demand ☒ Imminent Collision ☐ ______ ☐ ______	Aug cog mitigations are required for high stress, high demand situations (e.g., Fuchs et al., 2007). Imminent does not mean unavoidable here (unlike CIB).
Driver	☒ Yes ☐ No ☐ Unknown	☐ Head Position ☐ Glance ☐ Posture ☐ ______ ☐ ______	
______________	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ ______	
Transformation	**Applicable?**	**System Type**	**Notes**
Derivative System	☐ Yes ☒ No ☐ Unknown	☐ Drowsiness Fatigue ☐ CWS ☐ ______ ☐ ______ ☐ ______	
Detection Approach	☒ Yes ☐ No ☐ Unknown	☐ Visual Search ☐ Vehicle Control ☐ ______ ☐ ______ ☐ ______	
______________	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ ______	
Output	**Applicable?**	**Supported**	**Notes**
Driver State	☐ Yes ☒ No ☐ Unknown	☐ Visual Distraction ☐ Cognitive Distraction ☐ ______ ☐ ______ ☐ ______	
______________	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ ______	

Manufacturer: Augmented Cognition **Model Year:** NA ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Earcon Concept Source: Fuchs et. al. cites Barker, 2004 ☐ **Production** *or* ☒ **Research**

Detection - Function									
Input	**Applicable?**			**Information Streams**					**Notes**
Driver Data	☒ Yes	☐ No	☐ Unknown	☐ Pupil	☐ Eye Gaze	☐ Head Pose	☐ ____	☐ ____	
Vehicle Data	☒ Yes	☐ No	☐ Unknown	☐ Longitudinal Control	☐ Lateral Control	☐ CWS	☐ ____	☐ ____	
Environmental Data	☒ Yes	☐ No	☐ Unknown	☐ GPS Location	☐ Headlights	☐ ____	☐ ____	☐ ____	
Task Data	☒ Yes	☐ No	☐ Unknown	☐ Audio Status	☐ Phone Status	☒ IVIS Status	☐ ____	☐ ____	
____	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
____	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
Transformation	**General Algorithm Information**								
Algorithm	Machine Learning? ☒ Yes	☐ No	☐ Unknown	*Notes:*					
Output	**Applicable?**			**Driver State**					**Notes**
Driver State: Type	☒ Yes	☐ No	☐ Unknown	☐ Visual Distraction	☐ Cognitive Distraction	☐ Inattention	☒ stress	☒ workload	The mitigation could work better if driver state were system-specific
____	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
____	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	

Manufacturer: Augmented Cognition **Model Year:** NA ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Earcon Concept Source: Fuchs et. al. cites Barker, 2004 ☐ **Production** *or* ☒ **Research**

☐ Standard configuration ☐ Reconfigurable Notes:

Countermeasure-Purpose			
Output: Concurrent	**Applicable?**	**System Type**	**Notes**
Distraction Feedback	☐ Yes ☒ No ☐ Unknown	☐ Distraction Prevention ☐ Distraction Mitigation ☐ Collision Mitigation ☐ ______ ☐ _	
In-Vehicle Information Management	☒ Yes ☐ No ☐ Unknown	☒ Distraction Prevention ☐ Distraction Mitigation ☐ ______ ☐ ______ ☐ _	
CWS Adaptation	☐ Yes ☒ No ☐ Unknown	☐ Adaptive Passive Warning ☐ Shift to Active if Distracted ☐ Adaptive Active Assistance ☐ ______ ☐ _	
Attention Redirection	☐ Yes ☒ No ☐ Unknown	☐ Forward Hazard ☐ Peripheral Hazard ☐ Speed Control ☐ ______ ☐ _	
________________	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ _	
________________	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ _	
Output: Post-Drive	**Applicable?**	**System Type**	**Notes**
Behavioral Change	☐ Yes ☒ No ☐ Unknown	☐ Driver ☐ Fleet Manager ☐ ______ ☐ ______ ☐ _	
________________	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ _	
________________	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ _	
________________	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ _	

Manufacturer: Augmented Cognition **Model Year:** ______ ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Time critical target voice ☐ **Production** *or* ☒ **Research**

☒ Standard configuration ☐ Reconfigurable Notes:

Detection - Purpose

Input	Applicable?	Requirement	
Road Conditions	☐ Yes ☒ No ☐ Unknown	☐ Good visibility ☐ Visible Road Markings ☐ High Speed Roads ☐ ___ ☐ ___	
Vehicle Interior	☐ Yes ☒ No ☐ Unknown	☐ Ambient Illumination ☐ Sound Level ☐ ___ ☐ ___ ☐ ___	
Vehicle State	☒ Yes ☐ No ☐ Unknown	☒ Speed ☒ Traffic Demand ☒ Imminent Collision ☐ ___ ☐ ___	Vehicle state can provide time critical targets. Imminent does not mean unavoidable here (unlike CIB).
Driver	☐ Yes ☒ No ☐ Unknown	☐ Head Position ☐ Glance ☐ Posture ☐ ___ ☐ ___	
___	☐ Yes ☐ No ☐ Unknown	☐ ___ ☐ ___ ☐ ___ ☐ ___ ☐ ___	

Transformation	Applicable?	System Type	Notes
Derivative System	☐ Yes ☒ No ☐ Unknown	☐ Drowsiness Fatigue ☐ CWS ☐ ___ ☐ ___ ☐ ___	
Detection Approach	☒ Yes ☐ No ☐ Unknown	☐ Visual Search ☐ Vehicle Control ☒ time critical targets ☐ ___ ☐ ___	
___	☐ Yes ☐ No ☐ Unknown	☐ ___ ☐ ___ ☐ ___ ☐ ___ ☐ ___	

Output	Applicable?	Supported	Notes
Driver State	☐ Yes ☒ No ☐ Unknown	☐ Visual Distraction ☐ Cognitive Distraction ☐ ___ ☐ ___ ☐ ___	
___	☐ Yes ☐ No ☐ Unknown	☐ ___ ☐ ___ ☐ ___ ☐ ___ ☐ ___	

Manufacturer: Augmented Cognition **Model Year:** ______ ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Time critical target voice ☐ **Production** *or* ☒ **Research**

Detection - Function									
Input	**Applicable?**			**Information Streams**					**Notes**
Driver Data	☒ Yes	☐ No	☐ Unknown	☐ Pupil	☐ Eye Gaze	☐ Head Pose	☐ ____	☐ ____	The mitigation could work better if driver state were detected.
Vehicle Data	☒ Yes	☐ No	☐ Unknown	☐ Longitudinal Control	☐ Lateral Control	☒ CWS	☐ ____	☐ ____	
Environmental Data	☒ Yes	☐ No	☐ Unknown	☐ GPS Location	☐ Headlights	☒ time critical targets	☐ ____	☐ ____	
Task Data	☒ Yes	☐ No	☐ Unknown	☐ Audio Status	☐ Phone Status	☐	☐ ____	☐ ____	Task data - As with driver state, the mitigation could benefit from task data in terms of how it applies the voice modality augmentation.
____	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
____	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
Transformation	**General Algorithm Information**								
Algorithm	Machine Learning? ☒ Yes	☐ No	☐ Unknown	*Notes:*					
Output	**Applicable?**			**Driver State**					**Notes**
Driver State: Type	☒ Yes	☐ No	☐ Unknown	☐ Visual Distraction	☐ Cognitive Distraction	☐ Inattention	☐ ____	☐ ____	The mitigation could work better if driver state were detected The voice could specify the target or not.
____	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	.
____	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	

Manufacturer: Augmented Cognition **Model Year:** ______ ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Time critical target voice ☐ **Production** *or* ☒ **Research**

☐ Standard configuration ☐ Reconfigurable Notes:

Countermeasure-Purpose

Output: Concurrent	**Applicable?**	**System Type**	**Notes**
Distraction Feedback	☐ Yes ☒ No ☐ Unknown	☐ Distraction Prevention ☒ Distraction Mitigation ☐ Collision Mitigation ☐ ____ ☐ ____	
In-Vehicle Information Management	☒ Yes ☐ No ☐ Unknown	☐ Distraction Prevention ☐ Distraction Mitigation ☐ ____ ☐ ____ ☐ ____	
CWS Adaptation	☒ Yes ☐ No ☐ Unknown	☐ Adaptive Passive Warning ☐ Shift to Active if Distracted ☐ Adaptive Active Assistance ☐ ____ ☐ ____	
Attention Redirection	☒ Yes ☐ No ☐ Unknown	☐ Forward Hazard ☐ Peripheral Hazard ☐ Speed Control ☐ ____ ☐ ____	
____________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
____________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Output: Post-Drive	**Applicable?**	**System Type**	**Notes**
Behavioral Change	☐ Yes ☒ No ☐ Unknown	☐ Driver ☐ Fleet Manager ☐ ____ ☐ ____ ☐ ____	
____________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
____________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
____________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	

Manufacturer: NA **Model Year:** NA ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Eyes off forward display Source: Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006 (modified) ☐ **Production** *or* ☒ **Research**

☐ Standard configuration ☐ Reconfigurable Notes:

Detection - Purpose

Input	Applicable?	Requirement	Notes
Road Conditions	☐ Yes ☒ No ☐ Unknown	☐ Good visibility ☐ Visible Road Markings ☐ High Speed Roads ☐ ____ ☐ ____	
Vehicle Interior	☐ Yes ☐ No ☒ Unknown	☐ Ambient Illumination ☐ Sound Level ☐ ____ ☐ ____ ☐ ____	Because the algorithm is based on eye tracking sensor data, the limitations of the eye tracking system will impact the algorithm's performance
Vehicle State	☐ Yes ☒ No ☐ Unknown	☐ Speed ☐ Traffic Demand ☐ Imminent Collision ☐ Lane Marking ☐ ____	
Driver	☒ Yes ☐ No ☐ Unknown	☐ Head Position ☒ Glance ☐ Posture ☐ ____ ☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Transformation	**Applicable?**	**System Type**	**Notes**
Derivative System	☐ Yes ☒ No ☐ Unknown	☐ Drowsiness Fatigue ☐ CWS ☐ ____ ☐ ____ ☐ ____	
Detection Approach	☒ Yes ☐ No ☐ Unknown	☒ Visual Search ☐ Vehicle Control ☐ ____ ☐ ____ ☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Output	**Applicable?**	**Supported**	**Notes**
Driver State	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction ☐ Cognitive Distraction ☐ Inattention ☐ ____ ☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	

Manufacturer: NA **Model Year:** NA ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Eyes off forward display Source: Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006 (modified) ☐ **Production** *or* ☒ **Research**

☐ Standard configuration ☐ Reconfigurable Notes:

Detection - Function

Input	Applicable?	Information Streams	Notes
Driver Data	☒ Yes ☐ No ☐ Unknown	☐ Pupil ☒ Eye Gaze ☐ Head Pose ☐ ____ ☐ ____	
Vehicle Data	☐ Yes ☒ No ☐ Unknown	☐ Longitudinal Control ☐ Lateral Control ☐ CWS ☐ ____ ☐ ____	
Environmental Data	☐ Yes ☒ No ☐ Unknown	☐ GPS Location ☐ Headlights ☐ ____ ☐ ____ ☐ ____	
Task Data	☐ Yes ☒ No ☐ Unknown	☐ Audio Status ☐ Phone Status ☐ IVIS Status ☐ ____ ☐ ____	
________________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
________________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Transformation	**General Algorithm Information**		
Algorithm	Machine Learning? ☐ Yes ☒ No ☐ Unknown	*Notes:* A cumulative glance away from the roadway for 2 seconds within a 6 second running window defines visual distraction. The 6 second window is defined such that an identifiable action (i.e., lead vehicle braking) occurs during the fifth second. For the purpose of this study, to make the algorithm applicable for real time detection of distraction, a six-second window is used to accumulate glance duration away from the forward roadway.	
Output	**Applicable?**	**Driver State**	**Notes**
Driver State: Type	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction ☐ Cognitive Distraction ☐ Inattention ☐ ____ ☐ ____	
________________	☐ Yes ☐ No ☐ Unknown	☐ ☐ ☐ ☐ ☐	
________________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	

Manufacturer: NA **Model Year:** NA ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Multi-distraction detection Source: Victor 2010 (modified) ☐ **Production** *or* ☒ **Research**

☐ Standard configuration ☐ Reconfigurable Notes:

Detection - Purpose

Input	Applicable?	Requirement					
Road Conditions	☐ Yes ☒ No ☐ Unknown	☐ Good visibility	☐ Visible Road Markings	☐ High Speed Roads	☐ ____	☐ ____	
Vehicle Interior	☐ Yes ☐ No ☒ Unknown	☐ Ambient Illumination	☐ Sound Level	☐ ____	☐ ____	☐ ____	Because the algorithm is based on eye tracking sensor data, the limitations of the eye tracking system will impact the algorithm's performance
Vehicle State	☒ Yes ☐ No ☐ Unknown	☒ Speed	☐ Traffic Demand	☐ Imminent Collision	☐ Lane Marking	☐ ____	Speed used as a threshold for distraction detection: below 25 mph, algorithm is not activated, and once activated, speed must be 23 mph or higher. Speed also used to widen the road center cone at low speeds.
Driver	☒ Yes ☐ No ☐ Unknown	☒ Head Position	☒ Glance	☒ Posture	☐ ____	☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
Transformation	**Applicable?**	**System Type**					**Notes**
Derivative System	☐ Yes ☒ No ☐ Unknown	☐ Drowsiness Fatigue	☐ CWS	☐ ____	☐ ____	☐ ____	
Detection Approach	☒ Yes ☐ No ☐ Unknown	☒ Visual Search	☐ Vehicle Control	☐ ____	☐ ____	☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
Output	**Applicable?**	**Supported**					**Notes**
Driver State	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction	☒ Cognitive Distraction	☐ Inattention	☐ ____	☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐	☐	☐	☐	☐	

Manufacturer: NA **Model Year:** NA ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Multi-distraction detection Source: Victor 2010 (modified) ☐ **Production** *or* ☒ **Research**

☐ Standard configuration ☐ Reconfigurable Notes:

Detection - Function

Input	Applicable?	Information Streams	Notes
Driver Data	☒ Yes ☐ No ☐ Unknown	☐ Pupil ☒ Eye Gaze ☒ Head Pose ☒ Weight Distribution ☐ ________	Head then seat sensor data used if eye tracking data quality is poor. The difference between the left and right seat sensors was used to determine lateral shifts of the driver associated with reaching. If such a shift is sensed above a set threshold, it was interpreted as a glance away from the road center.
Vehicle Data	☐ Yes ☒ No ☐ Unknown	☐ Longitudinal Control ☐ Lateral Control ☐ CWS ☒ Speed ☐ _____	
Environmental Data	☐ Yes ☒ No ☐ Unknown	☐ GPS Location ☐ Headlights ☐ _____ ☐ _____ ☐ _____	
Task Data	☐ Yes ☒ No ☐ Unknown	☐ Audio Status ☐ Phone Status ☐ IVIS Status ☐ _____ ☐ _____	
________________	☐ Yes ☐ No ☐ Unknown	☐ _____ ☐ _____ ☐ _____ ☐ _____ ☐ _____	
________________	☐ Yes ☐ No ☐ Unknown	☐ _____ ☐ _____ ☐ _____ ☐ _____ ☐ _____	

Transformation	General Algorithm Information
Algorithm	Machine Learning? ☒ Yes ☐ No ☐ Unknown *Notes:* Based on percent road center, defined as most frequent gaze angle. When eyes outside of 10 degree cone for 3 sec (long glance), for 60% of a 17.3 sec window (glance history), or when in the cone for 83% of 60 second window (cognitive), either visual or cognitive distraction is indicated. Visual time sharing also calculated (4 sec running window) to improve reliability. Head tracking then seat pressure data used when quality is poor. Sensor type and speed are threshold adjusting variables. PRC windows are reset when distraction is indicated or when speed drops.

Output	Applicable?	Driver State	Notes
Driver State: Type	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction ☒ Cognitive Distraction ☐ Inattention ☐ _____ ☐ _	
________________	☐ Yes ☐ No ☐ Unknown	☐ ☐ ☐ ☐ ☐	
________________	☐ Yes ☐ No ☐ Unknown	☐ _____ ☐ _____ ☐ _____ ☐ _____ ☐ _	

Manufacturer: NA **Model Year:** NA ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Real-time Countermeasure — Uses modified Victor (2010) algorithm ☐ **Production** *or* ☒ **Research**

☐ Standard configuration ☐ Reconfigurable Notes:

Detection - Purpose

Input	Applicable?	Requirement	Notes
Road Conditions	☐ Yes ☒ No ☐ Unknown	☐ Good visibility ☐ Visible Road Markings ☐ High Speed Roads ☐ ______ ☐ ______	
Vehicle Interior	☐ Yes ☐ No ☒ Unknown	☐ Ambient Illumination ☐ Sound Level ☐ ______ ☐ ______ ☐ ______	Because the algorithm is based on eye tracking sensor data, the limitations of the eye tracking system will impact the algorithm's performance
Vehicle State	☒ Yes ☐ No ☐ Unknown	☒ Speed ☐ Traffic Demand ☐ Imminent Collision ☐ Lane Marking ☐ ______	Speed used as a threshold for distraction detection: below 25 mph, algorithm is not activated, and once activated, speed must be 23 mph or higher. Speed also used to widen the road center cone at low speeds.
Driver	☒ Yes ☐ No ☐ Unknown	☒ Head Position ☒ Glance ☒ Posture ☐ ______ ☐ ______	
______	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ ______	
Transformation	**Applicable?**	**System Type**	**Notes**
Derivative System	☐ Yes ☒ No ☐ Unknown	☐ Drowsiness Fatigue ☐ CWS ☐ ______ ☐ ______ ☐ ______	
Detection Approach	☒ Yes ☐ No ☐ Unknown	☒ Visual Search ☐ Vehicle Control ☐ ______ ☐ ______ ☐ ______	
______	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ ______	
Output	**Applicable?**	**Supported**	**Notes**
Driver State	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction ☒ Cognitive Distraction ☐ Inattention ☐ ______ ☐ ______	
______	☐ Yes ☐ No ☐ Unknown	☐ ______ ☐ ______ ☐ ______ ☐ ______ ☐ ______	

Manufacturer: NA **Model Year:** NA ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Real-time Countermeasure — Uses modified Victor (2010) algorithm ☐ **Production** *or* [X] **Research**

☐ Standard configuration ☐ Reconfigurable Notes:

Detection - Function

Input	Applicable?	Information Streams	Notes
Driver Data	[X] Yes ☐ No ☐ Unknown	☐ Pupil [X] Eye Gaze [X] Head Pose [X] Weight Distribution ☐ ________	Head then seat sensor data used if eye tracking data quality is poor. The difference between the left and right seat sensors was used to determine lateral shifts of the driver associated with reaching. If such a shift is sensed above a set threshold, it was interpreted as a glance away from the road center.
Vehicle Data	☐ Yes [X] No ☐ Unknown	☐ Longitudinal Control ☐ Lateral Control ☐ CWS ☐ _____ ☐ _____	
Environmental Data	☐ Yes [X] No ☐ Unknown	☐ GPS Location ☐ Headlights ☐ _____ ☐ _____ ☐ _____	
Task Data	☐ Yes [X] No ☐ Unknown	☐ Audio Status ☐ Phone Status ☐ IVIS Status ☐ _____ ☐ _____	
________________	☐ Yes ☐ No ☐ Unknown	☐ _____ ☐ _____ ☐ _____ ☐ _____ ☐ _____	
________________	☐ Yes ☐ No ☐ Unknown	☐ _____ ☐ _____ ☐ _____ ☐ _____ ☐ _____	
Transformation	**General Algorithm Information**		
Algorithm	Machine Learning? [X] Yes ☐ No ☐ Unknown	*Notes:* Based on percent road center, defined as most frequent gaze angle. When eyes outside of 10 degree cone for 3 sec (long glance), for 60% of a 17.3 sec window (glance history), or when in the cone for 83% of 60 second window (cognitive), either visual or cognitive distraction is indicated. Visual time sharing also calculated (4 sec running window) to improve reliability. Head tracking then seat pressure data used when quality is poor. Sensor type and speed are threshold adjusting variables. PRC windows are reset when distraction is indicated or when speed drops.	
Output	**Applicable?**	**Driver State**	**Notes**
Driver State: Type	[X] Yes ☐ No ☐ Unknown	[X] Visual Distraction [X] Cognitive Distraction ☐ Inattention ☐ _____ ☐ _____	
________________	☐ Yes ☐ No ☐ Unknown	☐ _____ ☐ _____ ☐ _____ ☐ _____ ☐ _____	
________________	☐ Yes ☐ No ☐ Unknown	☐ _____ ☐ _____ ☐ _____ ☐ _____ ☐ _____	

Manufacturer: NA **Model Year:** NA ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Real-time Countermeasure — Uses modified Victor (2010) algorithm ☐ **Production** *or* ☒ **Research**

☐ Standard configuration ☐ Reconfigurable Notes:

Countermeasure-Purpose

Output: Concurrent	Applicable?	System Type	Notes
Distraction Feedback	☒ Yes ☐ No ☐ Unknown	☐ Distraction Prevention ☒ Distraction Mitigation ☐ Collision Mitigation ☐ ____ ☐ ____	
In-Vehicle Information Management	☐ Yes ☒ No ☐ Unknown	☐ Distraction Prevention ☐ Distraction Mitigation ☐ ____ ☐ ____ ☐ ____	
CWS Adaptation	☐ Yes ☒ No ☐ Unknown	☐ Adaptive Passive Warning ☐ Shift to Active if Distracted ☐ Adaptive Active Assistance ☐ ____ ☐ ____	
Attention Redirection	☐ Yes ☒ No ☐ Unknown	☐ Forward Hazard ☐ Peripheral Hazard ☐ Speed Control ☐ ____ ☐ ____	
____________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
____________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Output: Post-Drive	**Applicable?**	**System Type**	**Notes**
Behavioral Change	☐ Yes ☒ No ☐ Unknown	☐ Driver ☐ Fleet Manager ☐ ____ ☐ ____ ☐ ____	
____________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
____________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
____________	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	

Manufacturer: NA **Model Year:** NA ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Real-time Countermeasure Uses modified Victor (2010) algorithm ☐ **Production** *or* ☒ **Research**

☐ Standard configuration ☐ Reconfigurable Notes:

Countermeasure-Function

Output: Concurrent	Applicable?			Specification					Notes
Distraction Alert Display Timing	☒ Yes	☐ No	☐ Unknown	☒ Real Time	☐ Delayed	☐ ____	☐ ____	☐ ____	
Distraction Alert Specificity	☒ Yes	☐ No	☐ Unknown	☒ Visual Distraction	☒ Cognitive Distraction	☐ Inattention	☐ ____	☐ ____	
Attention Feedback Presentation	☒ Yes	☐ No	☐ Unknown	☒ Discrete Alert	☐ Continuous Level	☐ ____	☐ ____	☐ ____	
Distraction Alert Modality	☒ Yes	☐ No	☐ Unknown	☒ Tone	☐ Voice	☒ Visual	☐ Haptic	☐ ____	
Distraction Alert Response Timing	☒ Yes	☐ No	☐ Unknown	☒ Milliseconds	☐ Seconds	☐ ____	☐ ____	☐ ____	
Distraction Alert Resolution	☒ Yes	☐ No	☐ Unknown	☒ Binary	☐ Graded	☐ ____	☐ ____	☐ ____	
In-Vehicle Information Management	☐ Yes	☒ No	☐ Unknown	☐ Vehicle Status	☐ Audio	☐ Telecom	☐ ____	☐ ____	
CWS Adaptation	☐ Yes	☒ No	☐ Unknown	☐ Delay if Attentive	☐ Adapt Passive Alert Intensity	☐ Adapt Active Assistance Force	☐ ____	☐ ____	
Attention Redirection Modality	☐ Yes	☒ No	☐ Unknown	☐ Tone	☐ Voice	☐ Visual	☐ Haptic	☐ ____	
________________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
Output: Post-Drive	**Applicable?**			**Specification**					**Notes**
Cumulative Feedback	☐ Yes	☒ No	☐ Unknown	☐ Quantitative	☐ Incident Replay	☐ ____	☐ ____	☐ ____	

Manufacturer: NA **Model Year:** NA ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Post Drive Countermeasure Uses modified Victor (2010) algorithm ☐ **Production** *or* ☒ **Research**

☐ Standard configuration ☐ Reconfigurable Notes:

Detection - Purpose

Input	**Applicable?**			**Requirement**					**Notes**
Road Conditions	☐ Yes	☒ No	☐ Unknown	☐ Good visibility	☐ Visible Road Markings	☐ High Speed Roads	☐ ____	☐ ____	
Vehicle Interior	☐ Yes	☐ No	☒ Unknown	☐ Ambient Illumination	☐ Sound Level	☐ ____	☐ ____	☐ ____	Because the algorithm is based on eye tracking sensor data, the limitations of the eye tracking system will impact the algorithm's performance
Vehicle State	☒ Yes	☐ No	☐ Unknown	☒ Speed	☐ Traffic Demand	☐ Imminent Collision	☒ Lane Marking	☐ ____	Speed used as a threshold for distraction detection: below 25 mph, algorithm is not activated, and once activated, speed must be 23 mph or higher. Speed also used to widen the road center cone at low speeds. Lane exceedence and longitudinal vehicle control included in feedback provided.
Driver	☒ Yes	☐ No	☐ Unknown	☒ Head Position	☒ Glance	☒ Posture	☐ ____	☐ ____	
____________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
Transformation	**Applicable?**			**System Type**					**Notes**
Derivative System	☐ Yes	☒ No	☐ Unknown	☐ Drowsiness Fatigue	☐ CWS	☐ ____	☐ ____	☐ ____	
Detection Approach	☒ Yes	☐ No	☐ Unknown	☒ Visual Search	☐ Vehicle Control	☐ ____	☐ ____	☐ ____	
____________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	
Output	**Applicable?**			**Supported**					**Notes**
Driver State	☒ Yes	☐ No	☐ Unknown	☒ Visual Distraction	☒ Cognitive Distraction	☐ Inattention	☐ ____	☐ ____	
____________	☐ Yes	☐ No	☐ Unknown	☐ ____	☐ ____	☐ ____	☐ ____	☐ ____	

Manufacturer: NA **Model Year:** NA ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Post Drive Countermeasure — Uses modified Victor (2010) algorithm ☐ **Production** *or* ☒ **Research**

☐ Standard configuration ☐ Reconfigurable Notes:

Detection - Function

Input	Applicable?	Information Streams	Notes
Driver Data	☒ Yes ☐ No ☐ Unknown	☐ Pupil ☒ Eye Gaze ☒ Head Pose ☒ Weight Distribution ☐ ____	Head then seat sensor data used if eye tracking data quality is poor. The difference between the left and right seat sensors was used to determine lateral shifts of the driver associated with reaching. If such a shift is sensed above a set threshold, it was interpreted as a glance away from the road center.
Vehicle Data	☐ Yes ☒ No ☐ Unknown	☐ Longitudinal Control ☐ Lateral Control ☐ CWS ☐ ____ ☐ ____	
Environmental Data	☐ Yes ☒ No ☐ Unknown	☐ GPS Location ☐ Headlights ☐ ____ ☐ ____ ☐ ____	
Task Data	☐ Yes ☒ No ☐ Unknown	☐ Audio Status ☐ Phone Status ☐ IVIS Status ☐ ____ ☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	

Transformation	General Algorithm Information	
Algorithm	Machine Learning? ☒ Yes ☐ No ☐ Unknown	*Notes:* Based on percent road center, defined as most frequent gaze angle. When eyes outside of 10 degree cone for 3 sec (long glance), for 60% of a 17.3 sec window (glance history), or when in the cone for 83% of 60 second window (cognitive), either visual or cognitive distraction is indicated. Visual time sharing also calculated (4 sec running window) to improve reliability. Head tracking then seat pressure data used when quality is poor. Sensor type and speed are threshold adjusting variables. PRC windows are reset when distraction is indicated or when speed drops.

Output	Applicable?	Driver State	Notes
Driver State: Type	☒ Yes ☐ No ☐ Unknown	☒ Visual Distraction ☒ Cognitive Distraction ☐ Inattention ☐ ____ ☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	

Manufacturer: NA **Model Year:** NA ☐ **Aftermarket** *or* ☐ **OEM**

System Name: Post Drive Countermeasure Uses modified Victor (2010) algorithm ☐ **Production** *or* ☒ **Research**

☐ Standard configuration ☐ Reconfigurable Notes:

Countermeasure-Purpose

Output: Concurrent	Applicable?	System Type	Notes
Distraction Feedback	☐ Yes ☒ No ☐ Unknown	☐ Distraction Prevention ☐ Distraction Mitigation ☐ Collision Mitigation ☐ ____ ☐ ____	
In-Vehicle Information Management	☐ Yes ☒ No ☐ Unknown	☐ Distraction Prevention ☐ Distraction Mitigation ☐ ____ ☐ ____ ☐ ____	
CWS Adaptation	☐ Yes ☒ No ☐ Unknown	☐ Adaptive Passive Warning ☐ Shift to Active if Distracted ☐ Adaptive Active Assistance ☐ ____ ☐ ____	
Attention Redirection	☐ Yes ☒ No ☐ Unknown	☐ Forward Hazard ☐ Peripheral Hazard ☐ Speed Control ☐ ____ ☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
Output: Post-Drive	**Applicable?**	**System Type**	**Notes**
Behavioral Change	☒ Yes ☐ No ☐ Unknown	☒ Driver ☐ Fleet Manager ☐ ____ ☐ ____ ☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	
____	☐ Yes ☐ No ☐ Unknown	☐ ____ ☐ ____ ☐ ____ ☐ ____ ☐ ____	

Manufacturer: NA **Model Year:** NA [ ] **Aftermarket** *or* [ ] **OEM**

System Name: Post Drive Countermeasure Uses modified Victor (2010) algorithm [ ] **Production** *or* [X] **Research**

Countermeasure-Function

Output: Concurrent	Applicable?	Specification	Notes
Distraction Alert Display Timing	[ ] Yes [X] No [ ] Unknown	[ ] Real Time [ ] Delayed [ ] ____ [ ] ____ [ ] ____	
Distraction Alert Specificity	[ ] Yes [X] No [ ] Unknown	[ ] Visual Distraction [ ] Cognitive Distraction [ ] Inattention [ ] ____ [ ] ____	
Attention Feedback Presentation	[ ] Yes [X] No [ ] Unknown	[ ] Discrete Alert [ ] Continuous Level [ ] ____ [ ] ____ [ ] ____	
Distraction Alert Modality	[ ] Yes [X] No [ ] Unknown	[ ] Tone [ ] Voice [ ] Visual [ ] Haptic [ ] ____	
Distraction Alert Response Timing	[ ] Yes [X] No [ ] Unknown	[ ] Milliseconds [ ] Seconds [ ] ____ [ ] ____ [ ] ____	
Distraction Alert Resolution	[ ] Yes [X] No [ ] Unknown	[ ] Binary [ ] Graded [ ] ____ [ ] ____ [ ] ____	
In-Vehicle Information Management	[ ] Yes [X] No [ ] Unknown	[ ] Vehicle Status [ ] Audio [ ] Telecom [ ] ____ [ ] ____	
CWS Adaptation	[ ] Yes [X] No [ ] Unknown	[ ] Delay if Attentive [ ] Adapt Passive Alert Intensity [ ] Adapt Active Assistance Force [ ] ____ [ ] ____	
Attention Redirection Modality	[ ] Yes [X] No [ ] Unknown	[ ] Tone [ ] Voice [ ] Visual [ ] Haptic [ ] ____	
____________	[ ] Yes [ ] No [ ] Unknown	[ ] ____ [ ] ____ [ ] ____ [ ] ____ [ ] ____	
Output: Post-Drive	**Applicable?**	**Specification**	**Notes**
Cumulative Feedback	[X] Yes [ ] No [ ] Unknown	[X] Quantitative [X] Incident Replay [ ] ____ [ ] ____ [ ] ____	Distraction level over drive (by distance travelled), distraction level score, video replay of distracted driving, detailed driving data for driving performance and inattention; all data compared with peer driver data

Appendix D: Distraction Phone Screening Questions

Inclusion Criteria: General Driving Questions

If a subject fails to meet one of the following criteria, proceed to Closing.

1) **Do you possess a valid U.S. drivers' license and have been a licensed driver for one year?**
   (Must answer YES)
2) **Other than vision restrictions, is your drivers' license free of restrictions?**
   (Must answer YES)
3) **Do you wear glasses or contacts while driving or for reading?**
   (If YES to above)

   Would you be able to wear only contacts to your visit?

   (Must answer YES)
4) **Do you drive at least 3,000 miles per year?**
   (Must answer YES)
5) **Are you between the ages: 25-50?**
   (Must answer YES)
6) **Are you able to drive without special equipment to help you drive such as pedal extensions, hand brake or throttle, spinner wheel knobs, seat cushion or booster seat?**
   (Must answer YES)
7) **Do you ever engage in the following or similar behaviors while driving: talking on your cell phone, sending or receiving text messages, eating, sending or receiving emails, or changing CDs?**
   (Must Answer YES)
8) **Would this be the first time you have you participated in a driving simulator study?**
   (If NO to above)

   Was the study about alcohol and driving?

   (Must answer NO)

   Was the study in the past 12 months?

   (Must answer NO)

Exclusion Criteria: General Health

(1) If the subject is female:

- **Are you, or is there any possibility that you are pregnant?**

Exclusion criteria:

- If pregnant or there is any possibility of being pregnancy

(2) Have you been diagnosed with a serious illness?

- If YES, is the condition still active?
- Are there any lingering effects?
  - If YES, do you care to describe?

Exclusion criteria:

- Cancer (receiving any radiation and/or chemotherapy treatment within last 6 months)
- Crohn's disease
- Hodgkin's disease
- Parkinson's disease
- Currently receiving any radiation and/or chemotherapy treatment

(3) Do you have Diabetes?

NOTE: Type II diabetes accepted if controlled (medicated and under the supervision of physician)

Exclusion criteria:

- Type I diabetes - insulin dependent
- Type II – **Uncontrolled** (see above)

(4) Do you suffer from a heart condition such as disturbance of the heart rhythm or have you had a heart attack or a pacemaker implanted within the last 6 months?

- If YES, please describe?

Exclusion criteria:

- History of ventricular flutter or fibrillation
- Systole requiring cardio version (atrial fibrillation may be acceptable if heart rhythm is stable following medical treatment or pacemaker implants)

(5) Have you ever suffered brain damage from a stroke, tumor, head injury, or infection?

- If YES, what are the resulting effects?
- Do you have an active tumor?
- Any visual loss, blurring or double vision?
- Any weakness, numbness, or funny feelings in the arms, legs or face?
- Any trouble swallowing or slurred speech?
- Any uncoordination or loss of control?
- Any trouble walking, thinking, remembering, talking, or understanding?

Exclusion criteria:

- A stroke within the past 6 months
- An active tumor
- Any symptoms still exist

(6) Have you ever been diagnosed with seizures or epilepsy?

- If YES, when did your last seizure occur?

Exclusion criteria:

- A seizure within the past 12 months

(7) Do you have Ménière's disease or any inner ear, dizziness, vertigo, hearing, or balance problems?

- Wear hearing aides - full correction with hearing aides acceptable
- If YES, please describe.
- **Ménière's disease** is a problem in the inner ear that affects hearing and balance. Symptoms can be low- pitched roaring in the ear (tinnitus), hearing loss, which may be permanent or temporary, and vertigo.
- **Vertigo** is a feeling that you or your surroundings are moving when there is no actual movement, described as a feeling of spinning or whirling and can be sensations of falling or tilting. It may be difficult to walk or stand and you may lose your balance and fall.

Exclusion criteria:

- Meniere’s disease
- Any recent history of inner ear, dizziness, vertigo, or balance problems

(8) Are you currently diagnosed with glaucoma or undergoing treatment for glaucoma?
Exclusion criteria: • Diagnosis of glaucoma • Currently being treated for glaucoma • Untreated glaucoma

(9) Do you currently have cataracts?
Exclusion criteria: • Has cataracts

(10) Do you currently have a sleep disorder such as sleep apnea, narcolepsy or Chronic Fatigue Syndrome? ➢ If YES, please describe.
Exclusion criteria: • Untreated sleep apnea • Narcolepsy • Chronic Fatigue Syndrome

(11) Do you have migraine or tension headaches that require you to take medication daily? ➢ If YES, please describe.
Exclusion criteria: • Any narcotic medications

(12) Do you currently have untreated depression, anxiety disorder, drug dependency, claustrophobia, or ADHD? ➢ If YES, please describe
Exclusion criteria: • Untreated depression and ADHD • Dependency or abuse of psychoactive drugs, illicit drugs, or alcohol • Agoraphobia, hyperventilation, or anxiety attacks

(13) Have you experienced any pain from neck or back injuries within the last year?

- If YES, is it current or chronic neck or back injury?

Exclusion criteria:

- Any current skeletal, muscular or neurological problems in neck or back regions
- Chronic neck and back pain
- Pinched nerves in neck or back
- Back surgery within last year

(14) Do you have any medial issues that would limit the range of motion of your right shoulder?

- If YES, is reaching into the back seat difficult?

Exclusion criteria:

- Can't reach into the back seat

(15) Are you currently taking any prescription or over the counter medications?

- If YES, what is the medication?
- Are there any warning labels on your medications, such as potential for drowsiness?

Exclusion criteria:

- Sedating medications or drowsiness label on medication UNLESS potential participant indicates they have been on the medication consistency for the last 6 months AND states they have NO drowsiness effects from this medication

(16) Do you experience any kind of motion sickness? • If YES, what were the conditions you experienced: when occurred (age), what mode of transportation, (boat, plane, train, car), and what was the intensity of your motion sickness? ➢ On a scale of 0 to 10**, how often** do you experience motion sickness with **0 = Never and 10 = Always** ➢ On a scale of 0 to 10, **how severe** are the symptoms when you experience motion sickness with **0 = Minimal and 10 = Incapacitated**
Typical Exclusion criteria: • One single mode of transportation where intensity is high and present • More than 2 to 3 episodes for mode of transportation where intensity is moderate or above • Severity and susceptibility scores rank high For this study: • Excluded if experience motion sickness

Appendix E: Recruitment E-Mail

Subject: Participants invited for driving study

THE
NATIONAL ADVANCED
DRIVING SIMULATOR

We are looking for participants to take part in a driving simulation study at the National Advanced Driving Simulator. Adults ages 25-50 are invited to participate in a study about distractions while driving. You would be required to attend 1 daytime or evening visit up to 3 ½ hours in length.

Must:

- Drive at least 3,000 miles per year.
- If you have a vision requirement on your license, must be able and willing to wear contact lenses when driving in the study.
- Have not participated in a driving simulation study in the past year or in previous alcohol and driving research studies conducted at the National Advanced Driving Simulator.
- Engage in driving distraction tasks while driving such as, talking on cell phone, sending or receiving text messages, eating, sending or receiving emails or changing CDs.

You will be paid for your time and effort.

For more information, call [redacted] or www.drivingstudies.com

Appendix F: Recruitment Web Site

Subject: Participants invited for driving study

THE
NATIONAL ADVANCED
DRIVING SIMULATOR

We are looking for participants to take part in a driving simulation study at the National Advanced Driving Simulator. Adults ages 25-50 are invited to participate in a study on driving distractions. You would be required to attend 1 daytime or evening visit up to 3 ½ hours in length.

Must:

- Drive at least 3,000 miles per year.
- If you have a vision requirement on your license, must be able and willing to wear contact lenses when driving in the study.
- Have not participated in a driving simulation study in the past year or in previous alcohol and driving research studies conducted at the National Advanced Driving Simulator.
- Engage in driving distraction tasks while driving such as, talking on cell phone, sending or receiving text messages, eating, sending or receiving emails or changing CDs.

You will be paid for your time and effort.

For more information, call [redacted] or www.drivingstudies.com

Appendix G: Specific Details of the Data Collection Protocol

Participants

Thirty-two participants balanced for gender between the ages of 25 and 50[2] will be recruited for this study. Since the wearing of eye glasses has been shown to impact the quality of eye data[3], participants will excluded if they wear eye glasses to drive or for reading, but not if they wear contacts. They will be required to have experience engaging in distracting activities while driving such as talking on the phone, texting, emailing, eating, and changing CDs. They must have a valid, unrestricted U.S. driver's license (exception for participants with a corrective lens restriction), for at least one year, drive at least 3,000 miles per year, and not have participated in a driving simulator study in the past 12 months. They must be in good general health, have normal hearing, and not use special devices (e.g., spinner knobs, booster seats, etc.) while driving. Because the proposed database has been used for a separate NHTSA-funded study (IMPACT), participants in that study will be excluded from participating in this study.

Apparatus and Driving Scenarios

The experimental drives will be conducted using a high-fidelity, motion-based driving simulator, the NADS-1. The simulator will have a Chevy Malibu cab that is equipped with eye-tracking hardware, active feel on steering, brake, accelerator pedal, and a fully operational dashboard. The cab is mounted in a 24-foot dome. The motion system on which the dome is mounted provides 400 square meters of horizontal and longitudinal travel and ±330 degrees of rotation. Each of the three front projectors has a resolution of 1600 x 1200; the five rear projectors have a resolution of 1024 x 768. The edge blending between projectors is five degrees horizontal. A Seeing Machines faceLAB version 4.0 with dash-mounted dual stereo head channels will be used for the research-grade eye tracking system. A single-camera head tracking system will also be used; the Seeing Machines Driver State Sensor (DSS) in-vehicle system. Graphics have a 60 Hz frame rate. Driving data will be collected at up to 240 Hz.

Distraction Tasks

These tasks are all deferrable and once the participant begins to engage in each one, they will have limited time to complete the task. The driver will have the opportunity to defer the start of each task if they so choose, the cue to initiate the task will be repeated every 10 seconds if the driver has not initiated the task by that time.

Visual/Manual Task

The visual/manual secondary task is based on the Arrows task applied in HASTE (Engström et al., 2005). The Arrows task was designed to require visual processing and some manual engagement, with minimal cognitive processing. Participants will be presented with matrices of arrows on a 3 inch LCD touch screen display (approximate size of an iPhone) located at least 15 degrees from the driver's vertical and horizontal viewing position, with a maximum separation of 30 degrees (Stevens, Quimby, Board, Kersloot, & Burns, 2002). Placement more than 30 degrees

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[2] This age group was a stable low crash risk per mile driven and was chosen to minimize within-group variability that might reduce the statistical power of the comparisons.

[3] The effect of eye glasses on eye tracking performance with a two-camera system as it relates to distraction detection will be assessed through a review of the eye data from the IMPACT project for the CD task. The effect of eye glasses on the single camera system will be assessed during integration.

generally requires head movements (Green, Levison, Paelke, & Serafin, 1994); placement less than 30 degrees is the standard defined by JAMA (Japan Automobile Manufacturers Association) for in-vehicle displays (Akamatsu, 2009). With the proposed placement, it is expected that a portion of the participants will be able to perform the task by only moving their eyes, whereas others will choose to move their heads to view the display. The matrices are populated with 4 rows of 4 objects and/or targets each. The target arrow – an arrow pointing upwards – will be described to participants before the drive. Objects are arrows pointing in varying orientations. The target/object arrangement will parallel the Difficulty 2 level used in HASTE (Figure). Participants are instructed to scan each matrix and determine if a target is present among an array of objects. When a determination of the target's presence is made, the participant touches a "yes" or "no" button on the touch screen display to indicate whether the target was present or absent. A target may or may not be present. A single target will be presented in the matrices that have targets (there will not be multiple targets per matrix). An audible tone will announce each presentation of a matrix. The display will clear when the task is completed.

Five matrices will be displayed in immediate succession, with a one-second break between each matrix. Each presentation of a matrix will last no more than 5 seconds in length for a maximum total of 25 seconds of possible task engagement. This more continuous presentation of matrices would provide a similar experience to reading a lengthy email or searching for an album and song that requires reading and scrolling on a smart phone or an mp3 player.

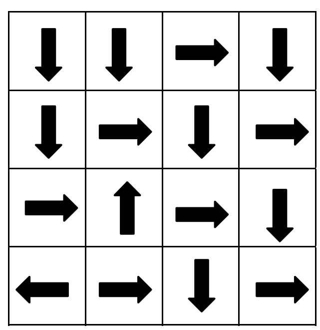

Figure G-1 Sample matrix for modified Arrows task

Incentive system

Performance on this task will be measured by the incentive calculation equations:

Delay	$\left[1 - \left(\frac{\text{Start Delay}}{\text{Startup Allowance}}\right)\right] \times 100$
Inattention	$\left[\left(\frac{\text{Number Completed}}{\text{Total Number}}\right)\right] \times 100$
Inaccurate	$\left[\left(\frac{\text{Number Correct}}{\text{Number Completed}}\right)\right] \times 100$
Total Score	$\left(\frac{\text{Delay} + \text{Inattention} + \text{Inaccurate}}{3}\right)$

Where:

Start Delay	The time delay from the start of the auditory cue until participant presses the “Start” button on the screen
Startup Allowance	A total of 10 seconds to engage in the arrows tasks
Total Number	The total number of matrices that could be responded to (5)
Number Competed	A count of the number of Arrow matrices to which the participant responds
Number Correct	A count of the number of Arrow matrices that the participant correctly identifies

Reaching Task

The reaching task is based on the Bee Catching task applied in the CWIM2 project. The task was designed as a visual/manual tracking task that requires a slight body turn, movement to the driver’s right when extending his/her arm, and full orientation of vision behind the passenger seat headrest (Figure G-2, Top). Participants will be presented with a bee moving aimlessly on a 12.1-inch LCD touch screen display. The display is mounted on an adjustable arm to accommodate differences in reach to the backseat between participants (Figure G-2, Bottom).

Figure G-2 Reaching task hardware setup; Top: head and body orientation; Bottom: display location and orientation.

A cover story will be presented to participants prior to the drive directing them to follow the path of an insect in the vehicle until the task ends. Participants will be trained to track the bug by touching the display and following it with a finger (Figure G-3). To encourage engagement with the task, participants will receive continuous feedback while tracking the bee: the finger touch trail will turn green to indicate that the participant is close to the bee and red to indicate a greater distance from the bee. Auditory feedback will also be provided, modulating based on performance: the buzzing sound of the bee will decrease when the participant’s finger is close to the bee, and increase when the distance between the finger and the bee is far away.

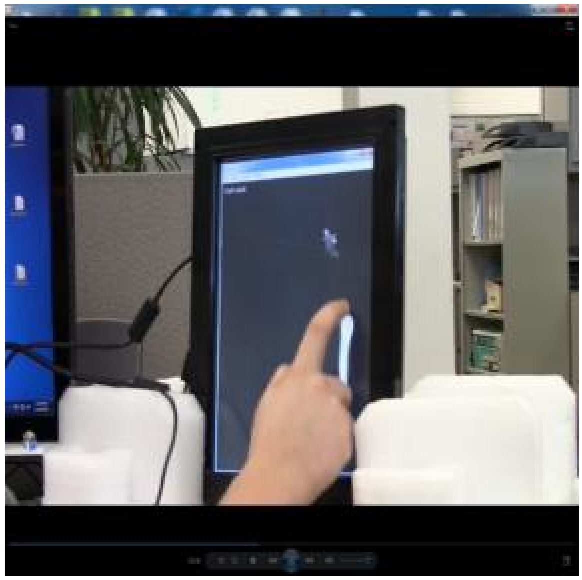

Figure G-3: Tracking insect with finger

The bee will appear on screen when prompted by a scenario trigger; a bee buzzing sound indicates the start of the task. When the task is complete, the buzzing sound stops and the application closes. To discourage participants from maintaining the side-oriented body position in anticipation of multiple presentations of this task, two 10-second presentations of the bee task will be separated by a 5-second break, for a total task time of approximately 25 seconds.

Incentive system

- Visual and auditory cues (green and red trails, modulation of buzzing) based on distance between finger and bee
- Performance on this task will be measured by the incentive calculation equations:

Delay	$\left[1-\left(\frac{\text{Start Delay}}{\text{Startup Allowance}}\right)\right]\times 100$
Inattention	$\left[1-\left(\frac{\text{Non Interaction Time}}{\text{Total Time}}\right)\right]\times 100$
Inaccurate	$(\text{Percent of Time in Green Zone})\times 100$
Total Score	$\left(\frac{\text{Delay } + \text{ Inattention } + \text{ Inaccurate}}{3}\right)$

Where:

Start Delay	The time delay from the start of the first bug buzz until the finger first touches the screen
Startup Allowance	A total of 10 seconds to engage in the bug tasks
Total Time	The total time of the bug task when the bug is active (20 seconds)
Non Interaction Time	Total time that the finger is either not touching the screen or not moving during the two interactions with the bug. This includes the time at the beginning of the second bug
Percent of Time in Green Zone	The total percentage of time when the finger is touching the screen that the following was in the green zone as defined by the task

Cognitive task

The complex cognitive task involves the participant traversing an interactive voice response (IVR) menu, similar to the Delta Flightline Task applied in the CAMP Driver workload metrics (DWM) project (Angell et al., 2006) or the MN511 menu task used in Rakauskas and Ward (2007). Following from Jacko and Salvendy (1996), complexity is introduced by incorporating depth in the hierarchical menu, which requires additional decision-making, response selection, and greater uncertainty of target locations along elongated paths. The use of interactive voice response menus increases demand on verbal working memory and auditory/vocal driver input/output modalities (Angell et al., 2006). In this task, participants will be instructed to obtain information using an IVR menu in order to answer a question asked at the beginning of each task presentation, similar to the procedures outlined in Angell et al. (2006) and Rakauskas and Ward (2007). A key piece of information (e.g., a flight number) will be given in the instructions along with the question, and participants will need to recall that information and make decisions based on it as they navigate through the menu nodes. A different question will be asked each time the task is presented. In addition to prompting decisions, questions will task short-term memory. Because this is purely a cognitive task, participants will be instructed to start the simulated call by saying “call <Destination>”; when information has been collected to answer the question, participants will be instructed to say “end call”. When the call is terminated, participants will vocalize the answer to the question. The order of the questions will be randomized. The task duration will be 25 seconds. Incorrect answers will yield an auditory cue.

For reference, the CAMP project used a commercial, interactive voice-response system supplied by Delta Airlines. An example of the dialogue used in the CAMP Delta Flightline task is given below (Figure G-4) A Wizard of Oz technique will be employed to eliminate the problems associated with voice recognition software.

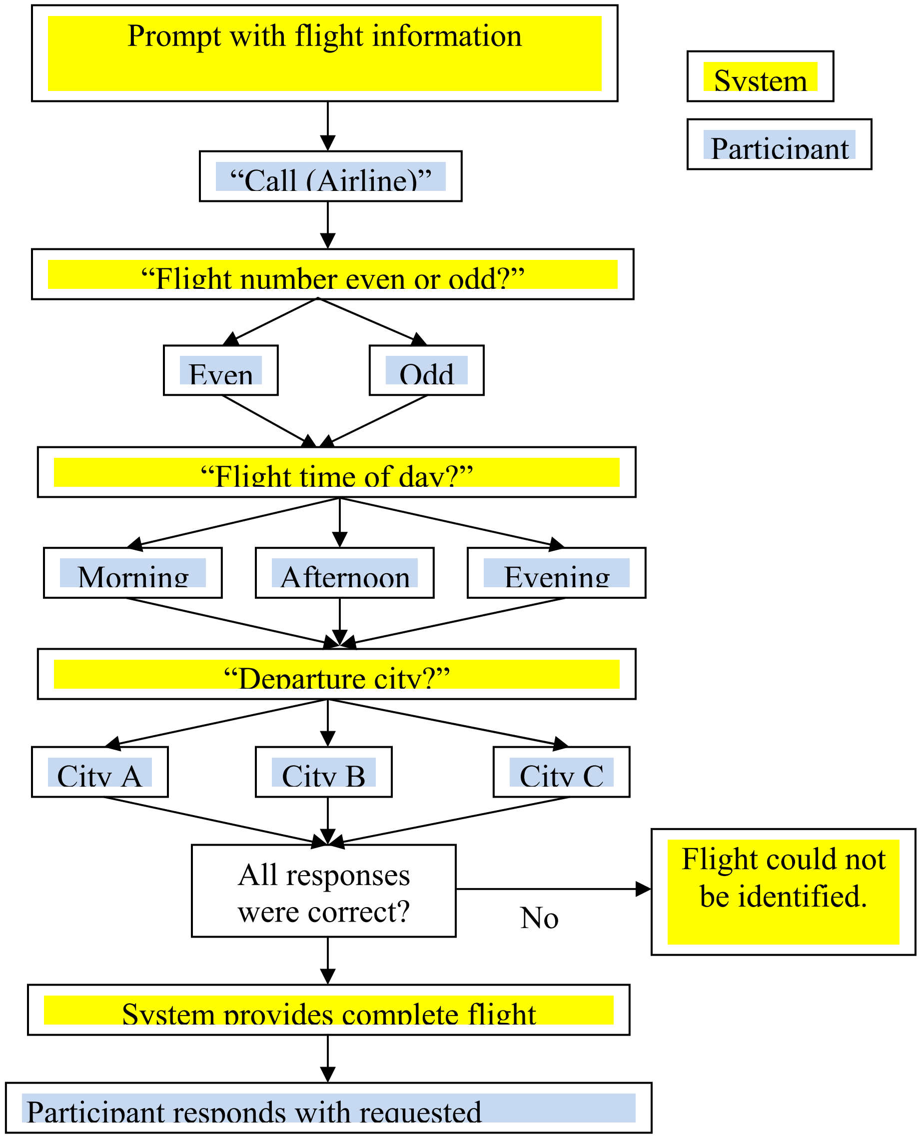

Figure G-4 Delta Flightline Example Dialogue

Incentive system

- Performance on this task will be measured by the incentive calculation equations:

Delay	$\left[1 - \left(\frac{\text{Start Delay}}{\text{Startup Allowance}}\right)\right] \times 100$
Inattention	$\left[\left(\frac{\text{Time to complete } - 25}{35 - 25}\right)\right] \times 100$
Inaccurate	$[(\text{Correct Final Answer})] \times 100$
Total Score	$\left(\frac{\text{Delay } + \text{ Inattention } + \text{ Inaccurate}}{3}\right)$

Where:

Start Delay	The time delay from the start of the first "Begin" Message until participant provides audio instruction to begin
Startup Allowance	A total of 10 seconds to engage in the cognitive menu tasks
Total Number	The total number of questions in the menu
Number Correct	A count of the number of Interim questions that the participant correctly answers
Correct Final Answer	Zero if incorrect, One if correct
Time to complete	The greater of the time from the first "begin" message to completion of the task or 25 seconds

Simple Self-Paced Visual/Manual Task

In addition to the three deferrable distraction tasks, the drive with distraction will include an ongoing simple visual/manual task, which consists of adjusting the setting on a radio. This will be designed as a self-paced visual/manual task that will provide some measure of the circumstances under which people allow themselves to be distracted. At the beginning of each of the three drive environments the ideal setting. The ideal setting will be defined by a numerical value on the radio's display; participants will be instructed on the ideal setting prior to the drive. The setting will vary accompanied by static that increases in volume during periods when other events are not occurring, but from the driver's perspective the task appears to occur over the duration of the drive. If the participant does not intervene before the beginning of the deferrable distraction tasks, the display drift will stop for the duration of the set of deferrable distraction tasks then resume again where it paused when the those task have finished. The timing and location of this task will be finalized in the scenario specification document. Participants will be instructed to use a touch screen display to adjust the radio setting up or down to the ideal setting. Participants will be shown the ideal setting prior to driving, and instructed to return the setting to the ideal setting when they notice the display has drifted.

Incentive system

- Performance on this task will be measured by the incentive calculation equations:

Delay	$\left[1-\left(\frac{\text{Start Delay}}{\text{Startup Allowance}}\right)\right]\times 100$
Inattention	$[(\text{Correct Adjustment})]\times 100$
Inaccurate	$\left[1-\left(\frac{\lvert Start\ Value - Final\ Value\rvert}{\lvert Start\ Value - Target\ Value\rvert}\right)\right]\times 100$
Total Score	$\left(\frac{\text{Delay} + \text{Inattention} + \text{Inaccurate}}{3}\right)$

Where:

Start Delay	The time delay from the start of the first increase in radio noise until participant provides an input, not counting the time when other distraction tasks are active
Startup Allowance	A total of 10 seconds to engage in the bug tasks
Correct Adjustment	Based on initial direction of adjustment: Zero if away from 50, One if towards 50
Start Value	The value of the noise when the driver responds
Final Value	The value of the noise when stops the adjustment
Target Value	The value to take the noise back to zero (50)

Order of distraction tasks

Using the Latin Square approach, there are two possible squares for balancing the order of the three distraction tasks. This provides six possible task orders to cover the eight instances in which tasks are to be performed. The orders were randomly assigned to the events without replacement until each of the six orders had been paired with an event. After this assignment, the urban drive and urban curves had not yet been paired with an order. Each of these was randomly paired with one of the six orders without replacement. The resulting combination of tasks to order of distraction tasks resulted in two repeated orders during the drive.

Incentive System

Because the purpose of this experiment is to validate and refine distraction detection algorithms, a feedback system will be used to encourage participants to engage in the deferrable and self-paced distracting tasks. The experimenter will provide scores out of 100 points to participants at the end of the three environments in the drive: prior to entering the interstate, between the interstate and the rural section at the stop sign, and at the end of the drive. Participants will receive a total score for that portion of the drive and at the end of the drive they will receive their cumulative score. The experimenter will communicate scores verbally. See the distraction tasks section above for implementation details for each distraction task type.

Instructions provided prior to the practice and main study drives will play an important role in defining for participants how they should prioritize driving vis-à-vis engagement in the secondary tasks. Participants will be instructed to complete as many tasks as possible while driving as they normally would. How task performance is measured will be explained to the participant, and a scale for task performance scores will be provided so participants can gauge their performance (e.g., score out of 100 points) and their overall task performance score at the end of the drive. Due to the lack of tasks in the baseline drive no performance feedback will be provided.

Dependent Variables

Table G-1 lists potential dependent measures. These will be refined as event specification details are finalized. Primary dependent measures include lateral and longitudinal control and eye movements. Eye tracking measures will be collected during the drive with special attention to the distribution of roadway and in-vehicle glances.

Table G-1 Objective dependent variables

Category	General indicator	Specific indicator	Comments
Driver control input	Steering wheel	Standard Deviation (SD) of Steering Wheel Angle	Simple and intuitive but not sensitive to cognitive distraction.
		Steering Wheel Reversal Rate	Simple and intuitive but could be sensitive to confounding environmental and age factors.
		Steering Entropy	Sensitive to distraction and has a high correlation with glance metrics.
		High Frequency component Steering Wheel Angle	Sensitive to variations in both primary and secondary task load.
	Brake pedal	Brake Reaction Time	Sensitive to cognitive and visual distraction but it is hard to define an event onset.
	Accelerator pedal	Throttle Hold	Sensitive to visual distraction but age factor and road type could influence metric's sensitivity.
Vehicle state	Lane position	SD of Lane Position	Common and intuitive indicator of distraction. A disadvantage is that environmental factors might either mask distraction when present or be perceived as distraction despite its absence.
	Speed	SD of Speed	More sensitive to visual distraction than cognitive distraction and could be sensitive to the environmental factors.
	Following time	SD of Headway	Sensitive to visual and cognitive distractions in car-following situations. Age could influence metric's sensitivity as well as traffic density and driver intent to engage in car following versus minimum headway maintenance.

Eye/head movement	Glance frequency	Mean/SD Glance Frequency	Could be sensitive to both visual and cognitive distractions.
	Glance duration	Mean/SD Percent Glance Durations >2s	Sensitive to visual distraction.
	Percent of gaze on road center	Mean/SD Percent Road Center	Could be sensitive to both visual and cognitive distractions.
	Percent of gaze off the road	M/SD Percent Off Road	Could be sensitive to both visual and cognitive distractions.
	Gaze direction	SD Horizontal (Gaze or Head)	Sensitive to visual distraction.
	Gaze direction	SD Vertical (Gaze or Head)	Sensitive to visual distraction.

Table G-2 Summary of events for the three segments of the drive

Environment	Proposed distraction events	Event name and (number)	Description	Challenge to driver
Urban	Radio	Pull Out (101)	Pull out of parallel parking spot into traffic	
	Menu Arrows Bug . . Radio	Urban Drive (102)	Drive on a narrow 2-lane road with traffic and parked vehicle	Driver's lateral and longitudinal control is expected to diminish
		Green Light (103)	Navigate green traffic light on urban 2-lane road with parked vehicles along the road, oncoming traffic, traffic behind driver	
	Arrows Bug Menu	Yellow Dilemma (104)	Navigate yellow light dilemma on urban two-lane with parked vehicle, oncoming traffic, traffic behind driver	Driver's ability to detect and react is expected to diminish
	Radio	Left Turn (105)	Left turn at signalized intersection (no green arrow, no dedicated turn lane),	Driver's ability to detect oncoming traffic and make a

			oncoming traffic, variety of gaps in traffic	decision is expected to diminish
	Arrows Menu Bug	Urban Curves (106)	Drive through three curve segments with mixed radius of curvature	Driver’s lateral control is expected to diminish
Freeway	Radio	Turn On Ramp (201)	Turn right onto interstate on-ramp	
	Radio	Merge On (202)	Merge onto interstate	
	Bug Menu Arrows	Following (203)	Intermittent slower-moving semi-truck traffic in the driving lane and a single slow moving passenger vehicle in the passing lane,	Driver’s lateral and longitudinal control are expected to diminish
	Radio	Merging Traffic (204)	Approach second interchange, interact with traffic merging into interstate	
	Menu Arrows Bug	Interstate Curves (205)	Navigate three curves on interstate	Driver’s lateral control is expected to diminish
	Radio	Exit Ramp (206)	Take exit ramp off interstate	
Rural	Bug Arrows Menu	Turn Off Ramp (301)	Turn right from ramp onto rural two-lane road	
		Lighted Rural (302)	Lighted two-lane rural road, 55 mph	Driver’s lateral control is expected to diminish
		Transition to Dark (303)	Short segment of road where lighting diminishes, 55 mph	-
	Menu Bug Arrows Radio	Dark Rural (304)	Dark straight and curved road~~,~~ segments, center and road edge marking are faded and the road surface is grayish; a hairpin turn and a vertical curve, 55 mph	Driver’s lateral control is expected to diminish more than under the distraction on lighted road
	Radio	Transition to Gravel (305)	Short transition between paved road and gravel road	
	Arrows Menu Bug Radio	Gravel Road (306)	Dark two-lane rural gravel road, straight and curved road segments, no center or edge markings	No road markings, possible increased variability in steering wheel angle and body position

Appendix H: Informed Consent Document

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IRB ID #: 200809743
APPROVAL DATE: 08/01/10
EXPIRATION DATE: 08/01/11

INFORMED CONSENT DOCUMENT

Project Title: **Distraction Detection and Mitigation through Driver Feedback**

Principal Investigator: **Jane Moeckli, PhD**

Research Team Contact: **Jane Moeckli, (319) 335-4672**

This consent form describes the research study to help you decide if you want to participate. This form provides important information about what you will be asked to do during the study, about the risks and benefits of the study, and about your rights as a research subject.

- If you have any questions about or do not understand something in this form, you should ask the research team for more information.
- You should discuss your participation with anyone you choose such as family or friends.
- Do not agree to participate in this study unless the research team has answered your questions and you decide that you want to be part of this study.

WHAT IS THE PURPOSE OF THIS STUDY?

This is a research study. We are inviting you to participate in this research study because you are between the ages of 25-50 years of age, have experience engaging in distracting activities while you drive, have a valid unrestricted US driver's license for at least 1 year, drive at least 3,000 miles per year, have not participated in a driving simulation study in the past 12 months, in good general health with normal hearing, and do not require any special equipment to help you drive.

The purpose of this research study is to evaluate various ways to detect and reduce driving distraction tasks.

HOW MANY PEOPLE WILL PARTICIPATE?

Approximately 96 people will take part in this study at the University of Iowa.

HOW LONG WILL I BE IN THIS STUDY?

If you agree to take part in this study, your involvement will last for one visit that will take approximately 3 hours.

WHAT WILL HAPPEN DURING THIS STUDY?

Upon arrival at the National Advanced Driving Simulator (NADS) at the University Research Park (formerly the Oakdale Campus), study staff will verbally review this document with you, answer any questions you may have about the study, and provide you time to read this document. If you agree to participate you will be asked to sign this document. You will receive a copy of this signed Informed Consent Document.

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EXPIRATION DATE: 08/01/11

Next, you will be asked to show your driver's license to confirm you have a valid U.S. driver's license and then fill out a payment form which asks for your social security number. Next, you will be asked to complete a questionnaire that covers some general demographic and driving information that includes questions about your driving history including the type of vehicles you drive, your license history, driving violations and accidents, and driving habits. We will also ask for your birth date, gender, ethnicity, marital status, highest level of education completed, employment information, and participation in other driving studies. This questionnaire also asks you several health related questions including medication, drug and alcohol use, and history of motion sickness.

Then you will be asked to watch a PowerPoint presentation on the computer that gives you an overview of the simulator cab and drive, the purpose of the study, the systems installed in the vehicle, and the tasks you may be asked to complete while driving. The tasks that you may be asked to complete involve reaching into the back passenger seat and following a moving display, identifying whether a target object is present on a computer display, making a call to a simulated interactive voice menu to retrieve flight information, and adjusting the setting on the radio back to a specified level.

Prior to entering the simulator, temporary stickers will be applied to your face so that we may track your eye and head movements while you drive. These stickers are commercially manufactured and are the same type of stickers that are given to children at doctor's offices. The eye tracking cameras are mounted on the vehicle dashboard and will record your head and eye movements during the drive by following the movement of the stickers. If you are allergic to latex, please inform study staff and we will use temporary tattoos in place of stickers containing latex. If tattoos are used, a damp cloth will be pressed upon the tattoo that is applied to your face for about 30 seconds after which the damp cloth and tattoo backing will be removed leaving the tattoo. If tattoos are used instead of stickers, you will be asked to remove the tattoos before leaving, using your choice of several available over the counter cleansers. The stickers will be removed at the end of the study drives.

Then you will be escorted into the simulator and asked to complete a practice drive approximately 8 minutes in length to get you comfortable with driving the simulator. The practice drive will allow you time to perform and practice the distraction tasks you will be asked to complete during the main drives. At the end of your practice drive you will receive feedback on your performance on the distraction tasks. Then you will be asked to rate your workload and how difficult you found maintaining your speed and lane position while performing the distraction tasks and while not engaging the distraction tasks during your drive on a touch screen tablet computer. After your practice drive you will be asked to complete a survey about how you feel at that time.

Next you will be asked to complete 2 study drives each approximately 30 minutes in length. During one study drive you will not engage in distraction tasks. The drive without distraction tasks may be either your first or second study drive. During the other study drive you will be asked to engage in four tasks that include reaching into the back passenger seat and following a moving display, identifying whether a target object is present on a computer display, making a call to a simulated interactive voice menu to retrieve flight information, and adjusting the setting on the radio back to a specified level. At three points during this study drive you will be asked to rate your workload and how difficult you found maintaining your speed and lane position while performing the distraction tasks and while not engaging the distraction tasks during your drive and you will receive feedback on your performance on the distraction tasks. At the end of your second study drive you will be asked to complete a questionnaire about how you feel.

After the final drive, you will be escorted back to the waiting room and asked to complete a questionnaire evaluating how real you viewed the simulator. A member of the research team will complete your payment form and you will be free to go.

You may skip any questions that you do not wish to answer on the questionnaires.

The simulator contains sensors that measure vehicle operation, vehicle motion, and your driving actions. The system also contains video cameras that capture images of you while driving (e.g., driver's hand position on the steering wheel, forward road scene, the direction of gaze). These sensors and video cameras are located in such a manner that they will not affect you or obstruct your view while driving. The information collected using these sensors and video cameras are recorded for analysis by research staff and may be used as described in the Confidentiality section below.

SOCIAL SECURITY NUMBER (SSN) USAGE

You will be asked to provide your social security number on the payment form that is then entered into the University of Iowa's Account Payable computer system. The payment form is shredded once your name, address, and social security number have been entered. The collection of your social security number is to be used only for payment of your time and effort for participating in this research study.

____ I allow you to collect and use my social security number for the purposes outlined above.

____ I do NOT allow you to collect or use my social security number for the purposes outlined above. (Initial your choice above)

WHAT ARE THE RISKS OF THIS STUDY?

You may experience one or more of the risks indicated below from being in this study. In addition to these, there may be other unknown risks, or risks that we did not anticipate, associated with being in this study.

The risk involving driving the simulator is possible discomfort associated with simulator disorientation. Some participants in driving simulator studies reported feeling uncomfortable during or after the simulator drive. These feelings were usually mild to moderate and consisted of slight uneasiness, warmth, or eyestrain. These effects typically last for only a short time, usually 10-15 minutes, after leaving the simulator. You may quit driving at any time if you experience any discomfort.

If you ask to quit driving as a result of discomfort, you will be allowed to quit at once. If you ask to quit driving due to discomfort, you will be escorted to a room, asked to sit and rest, and offered a beverage and snack. A trained staff member will determine if and when you will be allowed to leave. If you show

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few or no signs of discomfort, you will be able to go home or transportation will be arranged if you feel you are unable to drive home. If you experience anything other than slight effects, a follow-up call will be made to you 24 hours later to ensure you're not feeling ill effects.

In the rare event that normal exiting of the simulator is not available; you will need to exit the simulator through an alternative path. You will be assisted down a small ladder and escorted to a participant waiting room. This could pose a minimal risk if you have difficulty negotiating the ladder or walkway in the simulator bay.

An experimenter will be in the back seat of the simulator cab to ensure your safety while you drive.

Risks associated with latex stickers can be dryness, itching, burning, scaling, and lesions of the skin.

Risks associated with temporary tattoos can be mild skin irritation during removal.

WHAT ARE THE BENEFITS OF THIS STUDY?

You will not benefit from being in this study. However, we hope that, in the future, other people might benefit from this study through the information gained about detecting distraction while driving and how we can reduce various distraction tasks that will ultimately improve safety on our roadways.

WILL IT COST ME ANYTHING TO BE IN THIS STUDY?

You will not have any costs for being in this research study.

WILL I BE PAID FOR PARTICIPATING?

You will be paid for being in this research study. You will need to provide your social security number (SSN) in order for us to pay you. You may choose to participate without being paid if you do not wish to provide your social security number (SSN) for this purpose. You may also need to provide your address if a check will be mailed to you. If your social security number is obtained for payment purposes only, it will not be retained for research purposes.

You will be paid $60 for your time. You will be paid with a check sent to your home address that you provided on the payment voucher.

You may quit the study at any time, however if you choose to quit before completion of the study your compensation will be pro-rated based on the length of time you participated. You will then be compensated $5 for every 15 minutes you participated.

WHO IS FUNDING THIS STUDY?

The National Highway Traffic Safety Administration is the study sponsor and funding this research. The University of Iowa is receiving payments from the National Highway Traffic Safety Administration to support the activities that are required to conduct the study. No one on the research team will receive a direct payment or increase in salary from the National Highway Traffic Safety Administration for

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conducting this study.

WHAT ABOUT CONFIDENTIALITY?

We will keep your participation in this research study confidential to the extent permitted by law. However, it is possible that other people such as those indicated below may become aware of your participation in this study and may inspect and copy records pertaining to this research. Some of these records could contain information that personally identifies you.

- federal government regulatory agencies,
- auditing departments of the University of Iowa, and
- the University of Iowa Institutional Review Board (a committee that reviews and approves research studies)

To help protect your confidentiality, you will be assigned a study number which will be used instead of your name to identify all data collected for the study. The list linking your study number and name will be stored in a secure location and will be accessible only to the researchers at the University of Iowa. All records and data containing confidential information will be maintained in locked offices or on a secure password protected computer system that is accessible to the researchers, the study sponsor, and its agents. It is possible that persons viewing the video data may be able to identify you. Study documents will be kept in a locked cabinet within a secure building that can only be entered by research personnel. After completion of analysis, all hard copies except the Informed Consent Documents will be scanned, placed on a CD and placed into the NADS archival room that has limited access by designated archival personnel. The original Informed Consent Documents will be stored in the NADS archival room that has limited access by designated archival personnel.

The **engineering data** collected and recorded in this study (including any performance scores based on these data) will be analyzed along with data gathered from other participants. These data may be publicly released in final reports or other publications or media for scientific (e.g., professional society meetings), regulatory (e.g., to assist in regulating devices), educational (e.g., educational campaigns for members of the general public), outreach (e.g., nationally televised programs highlighting traffic safety issues), legislative (e.g., data provided to the U.S. Congress to assist with law-making activities), or research purposes (e.g., comparison analyses with data from other studies). Engineering data may also be released individually or in summary with that of other participants, but will not be presented publicly in a way that permits personal identification, except when presented in conjunction with video data.

The **video data** (video image data recorded during your drive) recorded in this study includes your video-recorded likeness and all in-vehicle audio including your voice (and may include, in some views, superimposed performance information). Video and in-vehicle sounds will be used to examine your driving performance and other task performance while driving. Video image data (in continuous video or still formats) and associated audio data may be publicly released, either separately or in association with the appropriate engineering data for scientific, regulatory, educational, outreach, legislative, or research purposes (as noted above).

The **simulator data** is captured and stored on hard drives located within a limited access area of the NADS facility. Access to simulator data is controlled through permissions established on a per-study basis.

If we write a report or article about this study, or share the study data set with others, we typically describe the study results in a summarized manner so that you cannot be identified by name.

IS BEING IN THIS STUDY VOLUNTARY?

Taking part in this research study is completely voluntary. You may choose not to take part at all. If you decide to be in this study, you may stop participating at any time. If you decide not to be in this study, or if you stop participating at any time, you won't be penalized or lose any benefits for which you otherwise qualify.

Can Someone Else End my Participation in this Study?
Under certain circumstances, the researchers might decide to end your participation in this research study earlier than planned. This might happen if you fail to operate the research vehicle in accordance with the instructions provided, or if there are technical difficulties with the driving simulator.

WHAT IF I HAVE QUESTIONS?

We encourage you to ask questions. If you have any questions about the research study itself, please contact: Jane Moeckli, 319-335-4672. If you experience a research-related injury, please contact Jane Moeckli, 319-335-4672.

If you have questions, concerns, or complaints about your rights as a research subject or about research related injury, please contact the Human Subjects Office, 105 Hardin Library for the Health Sciences, 600 Newton Rd, The University of Iowa, Iowa City, IA 52242-1098, (319) 335-6564, or e-mail irb@uiowa.edu. General information about being a research subject can be found by clicking "Info for Public" on the Human Subjects Office web site, http://research.uiowa.edu/hso. To offer input about your experiences as a research subject or to speak to someone other than the research staff, call the Human Subjects Office at the number above.

This Informed Consent Document is not a contract. It is a written explanation of what will happen during the study if you decide to participate. You are not waiving any legal rights by signing this Informed Consent Document. Your signature indicates that this research study has been explained to you, that your questions have been answered, and that you agree to take part in this study. You will receive a copy of this form.

Subject's Name (printed): ______________________________

Do not sign this form if today's date is on or after EXPIRATION DATE: 08/01/11 .

______________________________ ______________________________
(Signature of Subject) (Date)

FOR IRB USE ONLY
APPROVED BY: IRB-02
IRB ID #: 200809743
APPROVAL DATE: 08/01/10
EXPIRATION DATE: 08/01/11

Statement of Person Who Obtained Consent

I have discussed the above points with the subject or, where appropriate, with the subject's legally authorized representative. It is my opinion that the subject understands the risks, benefits, and procedures involved with participation in this research study.

____________________________________ __________________________
(Signature of Person who Obtained Consent) (Date)

Appendix I: Training Presentation

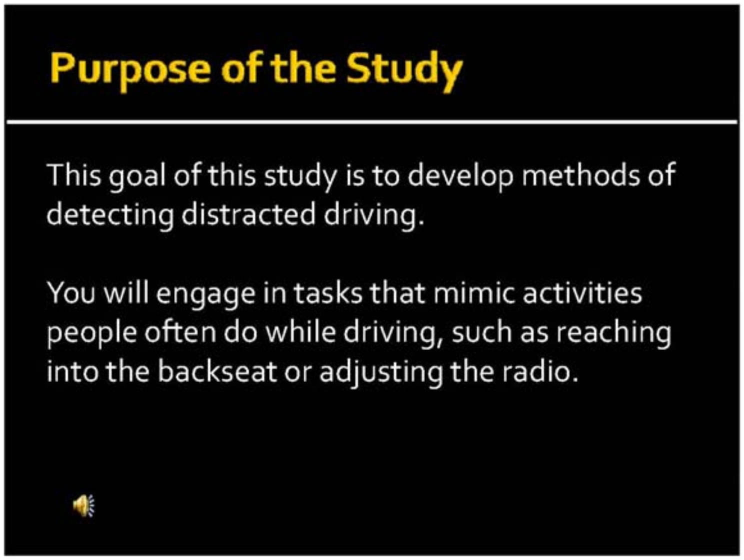
Pre-Drive Information for Study Participants

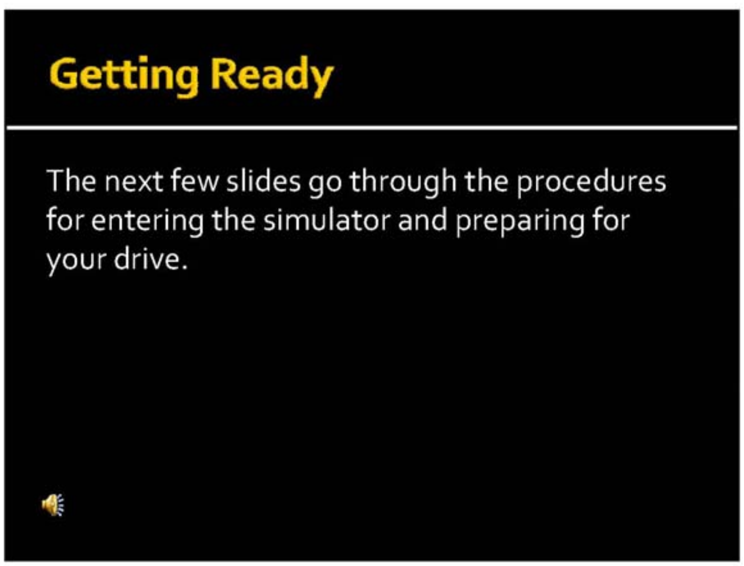
Distraction Study

Please press the space bar or use the
↓↑ keys to advance to a new slide.

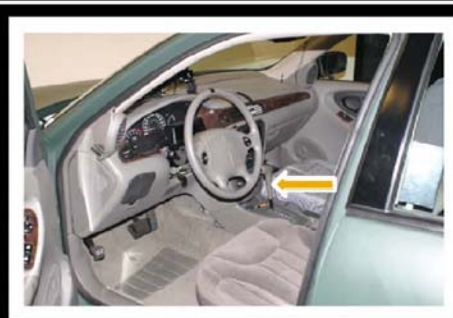
Instructions

Each slide will play on its own. Listen to each slide then go to the next slide when you are ready. You may ask questions at any time or at the end.


Purpose of the Study
This goal of this study is to develop methods of detecting distracted driving.
You will engage in tasks that mimic activities people often do while driving, such as reaching into the backseat or adjusting the radio.


Getting Ready
The next few slides go through the procedures for entering the simulator and preparing for your drive.

Interior



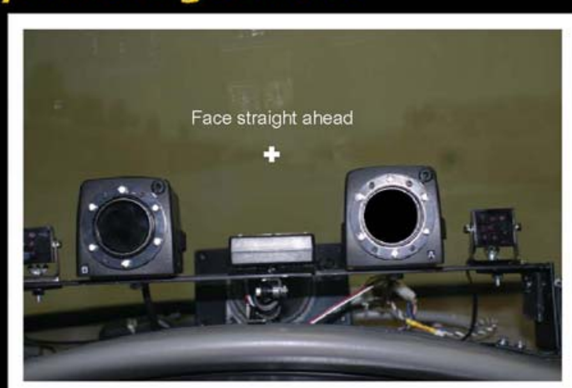
Seat Adjustments

Steering Wheel Adjustments

Fasten Seatbelt

Resting Position

Eye Tracking Cameras



Getting Comfortable in the Car

You may adjust the mirrors by using the control panel on the door. Set the side mirrors in much the same way as you would set the mirrors on your car. Wait to adjust the mirrors until after the eye tracking cameras have been calibrated. The control panel should be pressed firmly. If you need assistance, please ask the researcher in the simulator for help.

Intercom System

The car has an intercom system which allows the researchers to hear you. It is already adjusted for the drive today. If for any reason you want to stop driving, please tell us. The operator will hear you and can end the drive in just a few seconds.

Practice Drive

The drive starts with your car parked on an urban road. When told to begin, press on the brake, shift into drive, and begin to drive.

This drive is designed to help you get used to the simulator and allow you to practice the distraction tasks.

Navigation instructions will guide you through your route and a recording will tell you when it is time to stop.

Two Main Drives

After your practice drive, you will complete two more drives.
Both these drives start with your car parked on an urban road. You will drive through town, then enter a freeway, then exit onto a rural road.

Navigation instructions will guide you through your route and a recording will tell you when it is time to stop.

Click on the picture of the speaker to hear sample instructions.

During one main drive you will engage in tasks that will be described in later slides. During the other drive you will not engage in those tasks.

Your Destination

Tasks during your drives

At several points during one of your main drives you will engage in these tasks:

- Bug catching
- Arrows
- Flight information

Throughout your drive you will also monitor the setting of the radio and adjust it back to a specific level.

These tasks represent URGENT tasks that should be dealt with immediately. The goal is to complete as many tasks as you can while driving as you normally would.

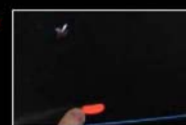
The following slides describe each of these tasks in more detail.

Bug Catching Task

When you hear buzzing, a virtual bug will appear on a touch screen located behind the passenger seat. Follow the bug by placing your finger on the touch screen where the bug is located. You must keep your finger on the screen and follow the path of the bug by tracing its path until you no longer hear it buzzing in the car. The buzzing will get more intense until you begin the task. **You must continue to follow the path of the bug with your finger until the buzz noise stops.**

You will see a GREEN glow around your finger if you are doing a good job tracing the path of the bug.

You will see a RED glow around your finger if you are *not* doing a good job tracing the path of the bug.



Maintain a GREEN glow.

Click on the picture of the speaker to hear the buzzing.

You will have a chance to practice in the car.

Arrows Task

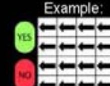
You will hear a prompt telling you to begin the Arrows task.
The prompt will play until you begin the task.
Click the picture of the speaker to hear the prompt.

You will press "Start" on the computer in the car.
A matrix of arrows will appear on the in-car computer screen.

Look at the display and decide if in "up" arrow ⬆ is one of the arrows.

If there is an "up" arrow then press "yes".
If there is *not* an "up" arrow then press "no".

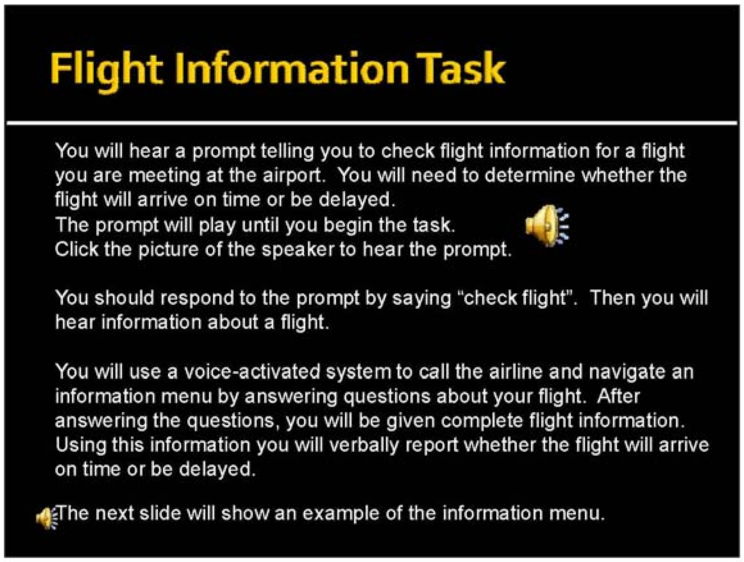
Example:

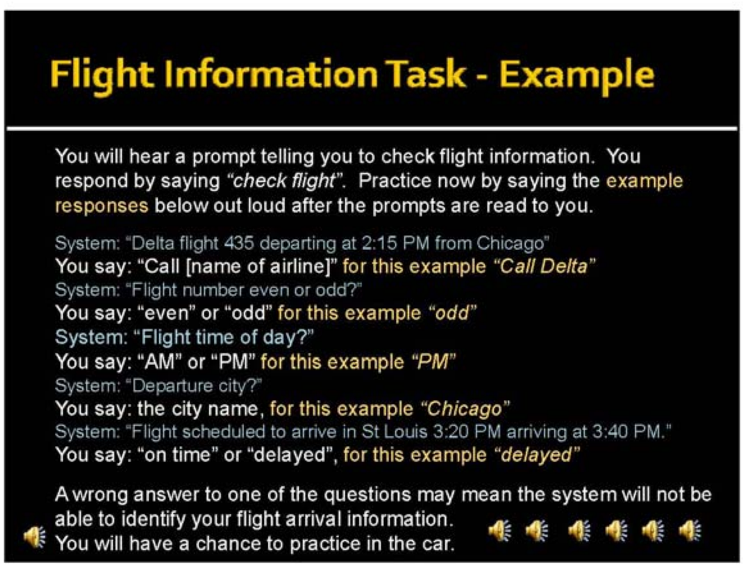


The goal is to get as many correct answers as possible.

A chime will play when another matrix appears after you have selected your answer. Click the picture of the speaker to hear the prompt.

You will have a chance to practice in the car.


Flight Information Task
You will hear a prompt telling you to check flight information for a flight you are meeting at the airport. You will need to determine whether the flight will arrive on time or be delayed.
The prompt will play until you begin the task.
Click the picture of the speaker to hear the prompt.
You should respond to the prompt by saying "check flight". Then you will hear information about a flight.
You will use a voice-activated system to call the airline and navigate an information menu by answering questions about your flight. After answering the questions, you will be given complete flight information. Using this information you will verbally report whether the flight will arrive on time or be delayed.
The next slide will show an example of the information menu.


Flight Information Task - Example
You will hear a prompt telling you to check flight information. You respond by saying "check flight". Practice now by saying the example responses below out loud after the prompts are read to you.
System: "Delta flight 435 departing at 2:15 PM from Chicago"
You say: "Call [name of airline]" for this example "Call Delta"
System: "Flight number even or odd?"
You say: "even" or "odd" for this example "odd"
System: "Flight time of day?"
You say: "AM" or "PM" for this example "PM"
System: "Departure city?"
You say: the city name, for this example "Chicago"
System: "Flight scheduled to arrive in St Louis 3:20 PM arriving at 3:40 PM."
You say: "on time" or "delayed", for this example "delayed"
A wrong answer to one of the questions may mean the system will not be able to identify your flight arrival information.
You will have a chance to practice in the car.

Appendix J: Driving Survey

Study: Distraction
Participant: _________
Date: _____________

Driving Survey

As part of this study, it is useful to collect information describing each participant. The following questions ask about you and your health and your driving patterns. Please read each question carefully. If something is unclear, ask the researcher for help. Your participation is voluntary and you have the right to omit questions if you choose. Please remember that all of your answers will be kept confidential.

Background Information

1) What is your birth date? _______ / _______ / ____________
Month Day Year

2) What age are you today? __________

3) What is your gender?
❒ Male
❒ Female

4) Of which ethnic origin(s) do you consider yourself? (Check all that apply)

❒ American Indian/Alaska Native
❒ Asian
❒ Black/African American
❒ Hispanic/Latino
❒ Native Hawaiian/Other Pacific Islander
❒ White/Caucasian
❒ Other

Continue to the next page

Study: Distraction
Participant: _________

Driving Experience

5) How old were you when you started to drive? ________ years of age

6) For which of the following do you currently hold a valid driver's license within the United States? (Check all that apply)

	Vehicle Type	Year When FIRST Licensed (May be Approximate)
❐	Passenger Vehicle License	____ ____ ____ ____
❐	Commercial Truck License	____ ____ ____ ____
❐	Motorcycle License	____ ____ ____ ____
❐	Other: ______________________	____ ____ ____ ____
❐	Other: ______________________	____ ____ ____ ____

7) How often do you drive? (Check the most appropriate category)

❐ Less than once weekly
❐ At least once weekly
❐ At least once daily

8) Approximately how many miles do you drive per year in each vehicle type, excluding miles driven for work-related activities? (Check only one for each vehicle)

Car	Motorcycle	Truck	Other: ____________
Do not drive	Do not drive	Do not drive	Do not drive
Under 2,000	Under 2,000	Under 2,000	Under 2,000
2,000 - 7,999	2,000 - 7,999	2,000 - 7,999	2,000 - 7,999
8,000 - 12,999	8,000 - 12,999	8,000 - 12,999	8,000 - 12,999
13,000 - 19,999	13,000 - 19,999	13,000 - 19,999	13,000 - 19,999
20,000 or more	20,000 or more	20,000 or more	20,000 or more

9) Is any driving you do work-related? (Check only one)

❐ No (Go to question # 10)
❐ Yes (please complete question 9a below)

9a) How many work-related miles do you drive per year? (Check only one)
❐ Under 2,000
❐ 2,000 - 7,999
❐ 8,000 - 12,999
❐ 13,000 - 19,999
❐ 20,000 or more

Continue to the next page

10) How frequently do you drive in the following environments? (Check only one for each environment)

	Never	Yearly	Monthly	Weekly	Daily
Residential	❒	❒	❒	❒	❒
Business District	❒	❒	❒	❒	❒
Rural Highway (e.g., Route 6)	❒	❒	❒	❒	❒
Interstate (e.g., Interstate 80)	❒	❒	❒	❒	❒
Gravel Roads	❒	❒	❒	❒	❒

11) What speed do you typically drive in a **residential area** when the speed limit is **25**?
__________mph

12) What speed do you typically drive in a **business district** when the speed limit is **35**?
________mph

13) What speed do you typically drive on a **rural highway** when the speed limit is **55**?
__________mph

14) What speed do you typically drive on the **Interstate** when the speed limit is **65?** __________mph

15) What speed do you typically drive on a **gravel road**? ___________mph

16) Have you ever had to participate in any driver improvement courses due to moving violations?

❒ No
❒ Yes (Please describe) ____

Continue to the next page

Study: Distraction
Participant: _________

17) When driving, how **frequently** do you perform each of the following tasks or maneuvers?

(Check the most appropriate answer for each task/maneuver)

	Never	Rarely	Occasionally	Frequently	Always	Not Applicable
Change lanes on Interstate or freeway	❒	❒	❒	❒	❒	❒
Keep up with traffic in town	❒	❒	❒	❒	❒	❒
Keep up with traffic on two-lane highway	❒	❒	❒	❒	❒	❒
Keep up with traffic on Interstate or freeway	❒	❒	❒	❒	❒	❒
Pass other cars on Interstate or freeway	❒	❒	❒	❒	❒	❒
Exceed speed limit	❒	❒	❒	❒	❒	❒
Wear a safety belt	❒	❒	❒	❒	❒	❒
Make left turns at uncontrolled intersections	❒	❒	❒	❒	❒	❒
Make or receive calls on your cell phone	❒	❒	❒	❒	❒	❒
Send or receive text messages	❒	❒	❒	❒	❒	❒
Send or receiving email	❒	❒	❒	❒	❒	❒
Eat	❒	❒	❒	❒	❒	❒
Change CDs	❒	❒	❒	❒	❒	❒
Reach into the back seat	❒	❒	❒	❒	❒	❒
Interact with a navigation system or electronic map	❒	❒	❒	❒	❒	❒

Continue to the next page

18) How **comfortable** do you feel when you drive in the following conditions or perform the following maneuvers? (Check the most appropriate answer for each condition)

	Very Uncomfortable	Slightly Uncomfortable	Slightly Comfortable	Very Comfortable	Not Applicable
Highway/freeway	❒	❒	❒	❒	❒
After drinking alcohol	❒	❒	❒	❒	❒
With children	❒	❒	❒	❒	❒
High-density traffic	❒	❒	❒	❒	❒
Passing other cars	❒	❒	❒	❒	❒
Changing lanes	❒	❒	❒	❒	❒
Making left turns at uncontrolled intersections	❒	❒	❒	❒	❒
Make or receive calls on your cell phone	❒	❒	❒	❒	❒
Send or receive text messages	❒	❒	❒	❒	❒
Send or receiving email	❒	❒	❒	❒	❒
Eat	❒	❒	❒	❒	❒
Change CDs	❒	❒	❒	❒	❒
Reach into the back seat	❒	❒	❒	❒	❒
Interact with a navigation system or electronic map	❒	❒	❒	❒	❒

Continue to the next page

Violations

19) Within the past five years, how many tickets have you received for the following? (Please check a response for each ticket)

	0	1	2	3+
Speeding	❒	❒	❒	❒
Going too slowly	❒	❒	❒	❒
Failure to yield right of way	❒	❒	❒	❒
Disobeying traffic lights	❒	❒	❒	❒
Disobeying traffic signs	❒	❒	❒	❒
Improper passing	❒	❒	❒	❒
Improper turning	❒	❒	❒	❒
Reckless driving	❒	❒	❒	❒
Following another car too closely	❒	❒	❒	❒
Operating While Intoxicated (OWI) or Driving Under the influence (DUI)	❒	❒	❒	❒
Cell phone, text messaging or distracted driving	❒	❒	❒	❒
Other (please specify **type** and **frequency** of violation) ____________________				

Continue to the next page

Accidents

20) In the past five years, how many times have you been the driver of a car involved in an accident?

- ❒ 0 (Go to question # 21 on page 8)
- ❒ 1
- ❒ 2
- ❒ 3
- ❒ 4 or more

Please provide the following information for each accident on the next page.

Continue to the next page

Study: Distraction
Participant: _________

Accident 1

Was another vehicle involved?	❒ No	❒ Yes
Was a pedestrian involved?	❒ No	❒ Yes
Were you largely responsible for this accident?	❒ No	❒ Yes
Did you go to driver's rehabilitation?	❒ No	❒ Yes
Weather Condition: ______________________	Month/Year: ______________________	
Description: ____		

Accident 2

Was another vehicle involved?	❒ No	❒ Yes
Was a pedestrian involved?	❒ No	❒ Yes
Were you largely responsible for this accident?	❒ No	❒ Yes
Did you go to driver's rehabilitation?	❒ No	❒ Yes
Weather Condition: ______________________	Month/Year: ______________________	
Description: ____		

Accident 3

Was another vehicle involved?	❒ No	❒ Yes
Was a pedestrian involved?	❒ No	❒ Yes
Were you largely responsible for this accident?	❒ No	❒ Yes
Did you go to driver's rehabilitation?	❒ No	❒ Yes
Weather Condition: ______________________	Month/Year: ______________________	
Description: ____		

Continue to the next page

8

Study: Distraction
Participant: __________

Other Studies

21) Have you participated in other driving studies?

❒ No (End of questionnaire)
❒ Yes (please provide details for each study you have participated in below)

Study 1
What vehicle was used for this study? (Check only one)

❒ Actual car - only
❒ Another simulator - only
❒ National Advanced Driving Simulator (Motion Simulator)
❒ National Advanced Driving Simulator (Static Simulator)
❒ Both - actual car and another simulator
❒ Both - actual car and the National Advanced Driving Simulator (Motion Simulator)

Brief Description:

____

____

Study 2
What vehicle was used for this study? (Check only one)

❒ Actual car - only
❒ Another simulator - only
❒ National Advanced Driving Simulator (Motion Simulator)
❒ National Advanced Driving Simulator (Static Simulator)
❒ Both - actual car and another simulator
❒ Both - actual car and the National Advanced Driving Simulator (Motion Simulator)

Brief Description:

____

____

Study 3
What vehicle was used for this study? (Check only one)

❒ Actual car - only
❒ Another simulator - only
❒ National Advanced Driving Simulator (Motion Simulator)
❒ National Advanced Driving Simulator (Static Simulator)
❒ Both - actual car and another simulator
❒ Both - actual car and the National Advanced Driving Simulator (Motion Simulator)

Brief Description:

____

____

Continue to the next page

Study: Distraction
Participant: _________

Health Status

21) How often do you experience motion sickness? (Circle only one)

0	1	2	3	4	5	6	7	8	9	10
Never										Always

23) How severe are your symptoms when you experience motion sickness (Circle only one)

0	1	2	3	4	5	6	7	8	9	10
None										Severe

24) Have you taken any medication in the past 48 hours? (Check only one)

❒ No
❒ Yes (Please list all) ____

____

24) Have you had any alcohol in the past 24 hours? (Check only one)

❒ No
❒ Yes (Please list all) ____

____

10

Appendix K: Workload and Subjective Rating Question stems

Workload and Subjective Rating Question Stems

Each of the following question stems will appear one at a time on the screen of a touch screen tablet computer. The rating will be gathered via a visual analog scale indicated by the line shown below. Participants will press the button for each distraction task to indicate which rating they are making and then make a slash across the line using a stylist. Participants may make the ratings in any order they choose.

Experimental Drive with Distraction Tasks

Workload

Please rate the workload you experienced during each of the following:

Arrows Task | Flight Information Task

Other times during drive | Bug Catching Task

Very Easy | Very Difficult

Lane Position

How difficult did you find staying in your lane during each of the following:

Arrows Task | Flight Information Task

Other times during drive | Bug Catching Task

Very Easy | Very Difficult

Speed Control

How difficult did you find maintaining your speed during each of the following:

Arrows Task | Flight Information Task

Other times during drive | Bug Catching Task

Very Easy | Very Difficult

Appendix L: Realism Survey

Study: Distraction
Participant:______

Date: _________

REALISM SURVEY

For each of the following items, circle the number that best indicates how closely the simulator resembles an actual car in terms of appearance, sound, and response. If an item is not applicable, circle NA.

	General Driving	Not at all realistic						Completely Realistic	
1	Response of the seat adjustment levers	0	1	2	3	4	5	6	NA
2	Response of the mirror adjustment levers	0	1	2	3	4	5	6	NA
3	Response of the door locks and handles	0	1	2	3	4	5	6	NA
4	Response of the fans	0	1	2	3	4	5	6	NA
5	Response of the gear shift	0	1	2	3	4	5	6	NA
6	Response of the brake pedal	0	1	2	3	4	5	6	NA
7	Response of accelerator pedal	0	1	2	3	4	5	6	NA
8	Response of the speedometer	0	1	2	3	4	5	6	NA
9	Response of the steering wheel while driving straight	0	1	2	3	4	5	6	NA
10	Response of the steering wheel while driving on curves	0	1	2	3	4	5	6	NA
11	Feel when accelerating	0	1	2	3	4	5	6	NA
12	Feel when braking	0	1	2	3	4	5	6	NA
13	Ability to read road and warning signs	0	1	2	3	4	5	6	NA
14	Appearance of car interior	0	1	2	3	4	5	6	NA
15	Appearance of signs	0	1	2	3	4	5	6	NA
16	Appearance of roads and road markings	0	1	2	3	4	5	6	NA
17	Appearance of urban scenery	0	1	2	3	4	5	6	NA
18	Appearance of rural scenery	0	1	2	3	4	5	6	NA
19	Appearance of freeway scenery	0	1	2	3	4	5	6	NA
20	Appearance of intersections	0	1	2	3	4	5	6	NA
21	Appearance of headlights	0	1	2	3	4	5	6	NA
22	Appearance of gravel road	0	1	2	3	4	5	6	NA
23	Appearance of other vehicles	0	1	2	3	4	5	6	NA
24	Appearance of rear-view mirror image	0	1	2	3	4	5	6	NA
25	Sound of the car	0	1	2	3	4	5	6	NA
26	Sound of other vehicles	0	1	2	3	4	5	6	NA
27	Overall feel of the car when driving	0	1	2	3	4	5	6	NA
28	Overall similarity to real driving	0	1	2	3	4	5	6	NA
29	Overall Appearance of driving scenes	0	1	2	3	4	5	6	NA

1

Study: Distraction
Participant:______

	Situational Driving	Not at all realistic					Completely Realistic	
30	Feel of driving straight while going 25 mph	0	1	2	3	4	5	6	NA
31	Feel of driving straight while going 35 mph	0	1	2	3	4	5	6	NA
32	Feel of driving straight while going 55 mph	0	1	2	3	4	5	6	NA
33	Feel of driving straight while going 65 mph	0	1	2	3	4	5	6	NA
34	Feel of driving on a curved road while going 25 mph	0	1	2	3	4	5	6	NA
35	Feel of driving on a curved road while going 55 mph	0	1	2	3	4	5	6	NA
36	Feel of driving on a curved road while going 65 mph	0	1	2	3	4	5	6	NA
37	Feel of accelerating from a stopped position	0	1	2	3	4	5	6	NA
38	Feel of braking to a stop	0	1	2	3	4	5	6	NA
39	Performing a 90 degree turn to the left while going 25 mph	0	1	2	3	4	5	6	NA
40	Performing a 90 degree turn to the right from a stopped position	0	1	2	3	4	5	6	NA
41	Feel of driving on the freeway	0	1	2	3	4	5	6	NA
42	Feel of changing lanes on the freeway	0	1	2	3	4	5	6	NA
43	Feel of driving on a freeway on/exit ramp	0	1	2	3	4	5	6	NA
44	Feel of driving on gravel road	0	1	2	3	4	5	6	NA
45	Ability to stop the vehicle	0	1	2	3	4	5	6	NA
46	Ability to respond to other vehicles	0	1	2	3	4	5	6	NA
47	Ability to keep straight in your lane	0	1	2	3	4	5	6	NA
48	Ability to respond at intersections	0	1	2	3	4	5	6	NA

2

Appendix M: Wellness Survey

Study: **Distraction**

Participant: ________

Date:________

#1

WELLNESS SURVEY

Directions: Circle one option for each symptom to indicate whether that symptom applies to you right now.

1. General Discomfort .... None .... Slight .... Moderate .... Severe
2. Fatigue .... None .... Slight .... Moderate .... Severe
3. Headache .... None .... Slight .... Moderate .... Severe
4. Eye Strain .... None .... Slight .... Moderate .... Severe
5. Difficulty Focusing .... None .... Slight .... Moderate .... Severe
6. Salivation Increased .... None .... Slight .... Moderate .... Severe
7. Sweating .... None .... Slight .... Moderate .... Severe
8. Nausea .... None .... Slight .... Moderate .... Severe
9. Difficulty Concentrating .... None .... Slight .... Moderate .... Severe
10. *"Fullness of the Head" .... None .... Slight .... Moderate .... Severe
11. Blurred Vision .... None .... Slight .... Moderate .... Severe
12. Dizziness with Eyes Open .... None .... Slight .... Moderate .... Severe
13. Dizziness with Eyes Closed ...... None .... Slight .... Moderate .... Severe
14. **Vertigo .... None .... Slight .... Moderate .... Severe
15. ***Stomach Awareness .... None .... Slight .... Moderate .... Severe
16. Burping .... None .... Slight .... Moderate .... Severe
17. Vomiting..................................... None .... Slight .... Moderate.........Severe
18. Other ________________ ..... None .... Slight .... Moderate.........Severe

* Fullness of the head is an awareness of pressure in the head.

**Vertigo is experienced as loss of orientation with respect to vertical upright.

***Stomach awareness is a feeling of discomfort which is just short of nausea.

Study: **Distraction**

Participant: ________

Date:_______

#2

WELLNESS SURVEY

Directions: Circle one option for each symptom to indicate whether that symptom applies to you right now.

1. General Discomfort .... None .... Slight .... Moderate .... Severe
2. Fatigue .... None .... Slight .... Moderate .... Severe
3. Headache .... None .... Slight .... Moderate .... Severe
4. Eye Strain .... None .... Slight .... Moderate .... Severe
5. Difficulty Focusing .... None .... Slight .... Moderate .... Severe
6. Salivation Increased .... None .... Slight .... Moderate .... Severe
7. Sweating .... None .... Slight .... Moderate .... Severe
8. Nausea .... None .... Slight .... Moderate .... Severe
9. Difficulty Concentrating .... None .... Slight .... Moderate .... Severe
10. *"Fullness of the Head" .... None .... Slight .... Moderate .... Severe
11. Blurred Vision .... None .... Slight .... Moderate .... Severe
12. Dizziness with Eyes Open .... None .... Slight .... Moderate .... Severe
13. Dizziness with Eyes Closed ...... None .... Slight .... Moderate .... Severe
14. **Vertigo .... None .... Slight .... Moderate .... Severe
15. ***Stomach Awareness .... None .... Slight .... Moderate .... Severe
16. Burping...................................... None .... Slight .... Moderate .... Severe
17. Vomiting.................................... None .... Slight .... Moderate.........Severe
18. Other ________________ ..... None .... Slight .... Moderate.........Severe

* Fullness of the head is an awareness of pressure in the head.

**Vertigo is experienced as loss of orientation with respect to vertical upright.

***Stomach awareness is a feeling of discomfort which is just short of nausea.

Appendix N: Distraction Detection Post-Drive Questionnaire

Study/Participant: _________

Date: ____________

Post-Drive Questionnaire

Please read each question carefully. If something is unclear ask the research assistant for help. You do not have to answer any questions you do not wish to answer.

The first few questions ask about a system that helps drivers avoid distraction by redirecting their attention to the roadway ***during*** their drive. This may take one or more forms, such as an audio tone, a flashing light, a vibration in the driver's seat, or other alert.

For each statement, circle the number that best corresponds to your level of agreement.

	Strongly Agree	Mildly Agree	Agree and Disagree Equally	Mildly Disagree	Strongly Disagree
1) Redirecting my attention to the roadway while driving would be helpful to me.	1	2	3	4	5
2) Other drivers in my household would benefit from an alert that redirected their attention to the roadway.	1	2	3	4	5
3) Alerts that redirect attention while driving would be disruptive.	1	2	3	4	5
4) Alerts that redirect attention while driving would be annoying.	1	2	3	4	5

The next few questions ask about a system that helps drivers avoid distraction by providing feedback ***after*** their drive. The feedback may take one or more forms, such as a percentage of time the driver may have been distracted, a map showing where the driver may have been distracted, or other measures of the driver's performance while driving.

For each statement, circle the number that best corresponds to your level of agreement.

	Strongly Agree	Mildly Agree	Agree and Disagree Equally	Mildly Disagree	Strongly Disagree
5) Feedback about distraction after driving would be helpful to me.	1	2	3	4	5
6) Other drivers in my household would benefit from feedback about distraction after driving.	1	2	3	4	5
7) Feedback after driving would be disruptive.	1	2	3	4	5
8) Feedback after driving would be annoying.	1	2	3	4	5

1

9) What kinds of alerts that redirected your attention to the roadway ***during*** a drive do you think would be helpful?

____

____

____

10) What kinds of feedback about distraction ***after*** a drive do you think would be helpful?

____

____

____

11) The next question asks about activities that may occur while driving that have the potential to take your attention away from the roadway. These activities may include talking on a cell phone, texting, attending to children/pets, changing the radio station, etc. For each, list an activity that typically happens when you drive, then answer the following questions about how you manage that activity.

ACTIVITY 1
List a typical activity that you do while driving that has the potential to take your attention away from the roadway:

____

How do you typically handle this activity while driving? (check all that apply)

❒ I ignore the activity.
❒ I always do this activity.
❒ I decide how urgent the activity is before choosing to do it or not.
❒ I find a way to do the activity that is less distracting for me. Please explain: ___________

____

❒ When doing this activity I continue driving as I normally would. My driving is not affected.
❒ I drive more carefully when doing this activity.
❒ I pull over and stop driving before doing this activity.
❒ I wait for a less demanding portion of my drive to do this activity.
❒ I wait until arriving at my destination to do this activity.
❒ Other, please explain:

____

____

ACTIVITY 2

List a typical activity that you do while driving that has the potential to take your attention away from the roadway:

____

How do you typically handle this activity while driving? (check all that apply)

❒ I ignore the activity.
❒ I always do this activity.
❒ I decide how urgent the activity is before choosing to do it or not.
❒ I find a way to do the activity that is less distracting for me. Please explain: ___________

____

❒ When doing this activity I continue driving as I normally would. My driving is not affected.
❒ I drive more carefully when doing this activity.
❒ I pull over and stop driving before doing this activity.
❒ I wait for a less demanding portion of my drive to do this activity.
❒ I wait until arriving at my destination to do this activity.
❒ Other, please explain:

____

____

ACTIVITY 3

List a typical activity that you do while driving that has the potential to take your attention away from the roadway:

____

How do you typically handle this activity while driving? (check all that apply)

❒ I ignore the activity.
❒ I always do this activity.
❒ I decide how urgent the activity is before choosing to do it or not.
❒ I find a way to do the activity that is less distracting for me. Please explain: ___________

____

❒ When doing this activity I continue driving as I normally would. My driving is not affected.
❒ I drive more carefully when doing this activity.
❒ I pull over and stop driving before doing this activity.
❒ I wait for a less demanding portion of my drive to do this activity.
❒ I wait until arriving at my destination to do this activity.
❒ Other, please explain:

____

____

12) What is the maximum price you would pay for a system that redirected your attention to the roadway ***while*** you were driving? ____________

13) What is the maximum price you would pay for a system that provided feedback about your level of distraction ***after*** your drive? ____________

14) At the actual price of $300, how likely would you be to consider purchasing a system that redirected your attention to the roadway ***while*** you were driving? (Circle one)

Definitely would **not** consider		Might or might not consider		Definitely would consider
1	2	3	4	5

15) At the actual price of $300, how likely would you be to consider purchasing a system that provided feedback about your level of distraction ***after*** your drive? (Circle one)

Definitely would **not** consider		Might or might not consider		Definitely would consider
1	2	3	4	5

16) Would you consider purchasing a distraction warning system if you received an insurance discount? (Circle one)

Definitely would **not** consider		Might or might not consider		Definitely would consider
1	2	3	4	5

17) Would you use a distraction warning system if it came standard on your vehicle? (Circle one)

Definitely would **not** consider		Might or might not consider		Definitely would consider
1	2	3	4	5

Appendix O: Distraction Detection Debriefing Statement

Thank you so much for participating in this study. Your participation was very valuable to us. We know you are very busy and appreciate the time you devoted to participating in this study.

In this study, we were interested in gathering driving data on distracted driving. We hope to be able to develop techniques to detect distracted driving based on this data. It is important that each person engages in the tasks during the drive, so we ask that you not discuss strategies for delaying or diverting the tasks with anyone else until the study is complete.

Our efforts will be greatly compromised if participants come into the study knowing ways to avoid the tasks. To this end, we would ask that you not discuss any of the details of the study until October 1, 2010.

Appendix P: Planned Behavior Questionnaire

Study/Participant: _________

Date: ____________

Planned Behavior Questionnaire

This survey asks about your plans to perform various behaviors while driving. You do not have to answer any questions you do not wish to answer. Unless other instructions are provided, circle the best answer for each question.

1. In the next week, how often do you expect to talk on your cellular phone while driving?

Never	Rarely	Moderately	Frequently	Always
0% of the time	1-33%	34-66%	67-99%	100% of the time

a. If your cellular phone rings while driving, how strongly do you feel the need to answer the call? (draw a vertical line across the scale)

____

Not at all Strong Moderately Strong Extremely Strong

b. If your cellular phone rings while driving, how strongly do you feel the need to see who is calling? (draw a vertical line across the scale)

____

Not at all Strong Moderately Strong Extremely Strong

c. If you miss a phone call while driving, how strongly do you feel the need to return the phone call while driving? (draw a vertical line across the scale)

____

Not at all Strong Moderately Strong Extremely Strong

d. If you have an unheard voicemail message, how strongly do you feel the need to listen to the voicemail message while driving? (draw a vertical line across the scale)

____

Not at all Strong Moderately Strong Extremely Strong

e. In the next week, how often do you think your peer driver (someone of the same age, gender, occupation, or driving experience) will talk on the cell phone while driving?

Never	Rarely	Moderately	Frequently	Always
0% of the time	1-33%	34-66%	67-99%	100% of the time

2. In the next week, how often do you expect to text on your cellular phone while driving?

Never	Rarely	Moderately	Frequently	Always
0% of the time	1-33%	34-66%	67-99%	100% of the time

a. If you receive a text while driving, how strongly do you feel the need to read the text? (draw a vertical line across the scale)

____

Not at all Strong Moderately Strong Extremely Strong

b. If you receive a text while driving, how strongly do you feel the need to see who is texting you? (draw a vertical line across the scale)

____

Not at all Strong Moderately Strong Extremely Strong

c. If you receive a text while driving, how strongly do you feel the need to respond to the text? (draw a vertical line across the scale)

____

Not at all Strong Moderately Strong Extremely Strong

d. In the next week, how often do you think your peer driver will text on the cellular phone while driving?

Never	Rarely	Moderately	Frequently	Always
0% of the time	1-33%	34-66%	67-99%	100% of the time

3. In the next week, how often do you expect to change a radio station, CD, or song on an MP3 player while driving?

Never	Rarely	Moderately	Frequently	Always
0% of the time	1-33%	34-66%	67-99%	100% of the time

   a. In the next week, how often do you think your peer driver will change a radio station, CD, or song on an MP3 player while driving?

Never	Rarely	Moderately	Frequently	Always
0% of the time	1-33%	34-66%	67-99%	100% of the time

4. In the next week, how often do you expect to eat or drink while driving?

Never	Rarely	Moderately	Frequently	Always
0% of the time	1-33%	34-66%	67-99%	100% of the time

   a. In the next week, how often do you think your peer driver will eat or drink while driving?

Never	Rarely	Moderately	Frequently	Always
0% of the time	1-33%	34-66%	67-99%	100% of the time

5. In the next week, how often do you expect to look at a map or navigation system while driving?

Never	Rarely	Moderately	Frequently	Always
0% of the time	1-33%	34-66%	67-99%	100% of the time

   a. In the next week, how often do you think your peer driver will look at a map or navigation system while driving?

Never	Rarely	Moderately	Frequently	Always
0% of the time	1-33%	34-66%	67-99%	100% of the time

6. In the next week, how often do you expect to put off doing a distracting task until you arrive at a stop sign or stop light?

Never	Rarely	Moderately	Frequently	Always
0% of the time	1-33%	34-66%	67-99%	100% of the time

7. In the next week, how often do you expect to put off doing a distracting task until there are fewer cars on the road?

Never	Rarely	Moderately	Frequently	Always
0% of the time	1-33%	34-66%	67-99%	100% of the time

8. In the next week, how often do you expect to put off doing in a distracting task until you pull over on the side of the road?

Never	Rarely	Moderately	Frequently	Always
0% of the time	1-33%	34-66%	67-99%	100% of the time

9. In the next week, how often do you expect to put off doing a distracting task until after you enter the highway/freeway?

Never	Rarely	Moderately	Frequently	Always
0% of the time	1-33%	34-66%	67-99%	100% of the time

10. In the next week, how often do you expect to turn off devices that could potentially distract you while driving?

Never	Rarely	Moderately	Frequently	Always
0% of the time	1-33%	34-66%	67-99%	100% of the time

Appendix Q: Performance Questionnaire

Date: _________

PERFORMANCE QUESTIONNAIRE – URBAN #2

During this segment of your drive, you were presented with several tasks. This questionnaire asks you about those tasks, your driving performance, and your thoughts about peer drivers' performance. You do not have to answer any questions you do not wish to answer.

Remember, one task equals:

- **A series of arrows matrices**
- **Tracking the bug two times with a break of a few seconds between its buzzing**
- **One flight information voice menu**

1. Of the 9 tasks presented during this portion of the drive, based on accuracy, continuous attention, and promptness, how well did you perform? (circle the best answer)

0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Poor										Excellent

   a. How confident are you in your response above? (draw a vertical line along scale)

   ____

   0% 50% 100%

   b. Based on accuracy, continuous attention, and promptness, how well do you think your peer (someone of the same age, gender, occupation, or driving experience) completing this same study would perform on the tasks? (circle the best answer)

0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Poor										Excellent

2. How often did you leave your lane unintentionally (i.e., at least one vehicle tire crosses the lane marking)? (circle the best answer)

0	1	2	3	4	5	6	7	8	9	10
times										times

   a. How confident are you in your response above? (draw a vertical line along scale)

   ____

   0% 50% 100%

1

b. How often do you think your peer completing this same study would leave their lane unintentionally? (circle the best answer)

0	1	2	3	4	5	6	7	8	9	10
times										times

3. What percent of the time did you drift above or below the speed limit? (circle the best answer)

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

a. How confident are you in your response above? (draw a vertical line along scale)

0% 50% 100%

b. What percent of the time do you think your peer completing this same study would drift above or below the speed limit? (circle the best answer)

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

4. What percent of the time did you look at the forward roadway (i.e. through the windshield) while doing the task? (circle the best answer)

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

a. How confident are you in your response above? (draw a vertical line along scale)

0% 50% 100%

b. What percent of the time do you think your peer completing this same study would look at the forward roadway while doing the task? (circle the best answer)

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

5. Please rate your overall task performance while driving. (draw a vertical line along scale)

Extremely Bad Average Extremely Good

6. Please rate your overall lane keeping performance. (draw a vertical line along scale)

Extremely Bad Average Extremely Good

7. Please rate your ability to maintain a safe, constant, and appropriate speed. (draw a vertical line along scale)

Extremely Bad Average Extremely Good

8. Please rate your ability to keep your eyes on the forward roadway. (draw a vertical line along scale)

Extremely Bad Average Extremely Good

9. Please rate your overall driving performance. (draw a vertical line along scale)

Extremely Bad Average Extremely Good

Appendix R: Distraction Mitigation Post-Drive Questionnaire (Mitigation)

Study/Participant: __________

Date: ______________

Post-Drive Questionnaire

Now that you have experience using a distraction warning system, we would like to know your opinion of the system. Please answer the following questions based on your expectation of using the warning system. If something is unclear ask the research assistant for help. You do not have to answer any questions you do not wish to answer.

The first two questions ask you to answer according to how strongly you agree or disagree with the statement. Please read each statement carefully before answering. To answer, check only one box for each statement that best expresses your answer.

1. Using the distraction warning system…

	Strongly Agree	Agree	Slightly Agree	Neutral	Slightly Disagree	Disagree	Strongly Disagree
a) … makes me a safer driver	□	□	□	□	□	□	□
b) … makes it easier to drive	□	□	□	□	□	□	□
c) … makes me more aware of the driving situation (other vehicles, lane position, etc.)	□	□	□	□	□	□	□
d) … reduces speeding events	□	□	□	□	□	□	□
e) … reduces distractions	□	□	□	□	□	□	□
f) … reduces lane departures	□	□	□	□	□	□	□
g) … improves my driving	□	□	□	□	□	□	□

2. The distraction warning system …

	Strongly Agree	Agree	Slightly Agree	Neutral	Slightly Disagree	Disagree	Strongly Disagree
a) … is easy to use	□	□	□	□	□	□	□
b) … is easy to learn	□	□	□	□	□	□	□
c) … is easy to understand	□	□	□	□	□	□	□
d) … is annoying	□	□	□	□	□	□	□
e) … is distracting	□	□	□	□	□	□	□

3. What is the maximum price you would pay for a distraction warning system like the one you used during your study drive? ____________

4. At the actual price of $300, how likely would you be to consider purchasing a distraction warning system like the one you used during your study drive? (Circle one)

Definitely would **not** consider		Might or might not consider		Definitely would consider
1	2	3	4	5

5. Would you consider purchasing a distraction warning system if you received an insurance discount? (Circle one)

Definitely would **not** consider		Might or might not consider		Definitely would consider
1	2	3	4	5

6. Would you use a distraction warning system if it came standard on your vehicle? (Circle one)

Definitely would **not** consider		Might or might not consider		Definitely would consider
1	2	3	4	5

APPENDIX S: DISTRACTION MITIGATION POST-DRIVE QUESTIONNAIRE (NO MITIGATION)

NM Study/Participant: _________

Date: _____________

Post-Drive Questionnaire

We would like to know your opinion about systems that mitigate, or lessen, driver distraction. Please read each statement carefully before answering. If something is unclear ask the research assistant for help. You do not have to answer any questions you do not wish to answer.

The first two questions ask about a system that helps drivers avoid distraction by redirecting their attention to the roadway ***during*** their drive. This may take one or more forms, such as an audio tone, a flashing light, a vibration in the driver's seat, or other alert.

Answer according to how strongly you agree or disagree with the statement. To answer, check only one box for each statement that best expresses your answer.

1. Using the distraction warning system that redirects my attention to the roadway when I'm distracted…

	Strongly Agree	Agree	Slightly Agree	Neutral	Slightly Disagree	Disagree	Strongly Disagree
a) … would make me a safer driver	□	□	□	□	□	□	□
b) … would make it easier to drive	□	□	□	□	□	□	□
c) … would make me more aware of the driving situation (other vehicles, lane position, etc.)	□	□	□	□	□	□	□
d) … would reduce speeding events	□	□	□	□	□	□	□
e) … would reduce distractions	□	□	□	□	□	□	□
f) … would reduce lane departures	□	□	□	□	□	□	□
g) … would improve my driving	□	□	□	□	□	□	□

2. The distraction warning system that redirects my attention to the roadway when I'm distracted …

	Strongly Agree	Agree	Slightly Agree	Neutral	Slightly Disagree	Disagree	Strongly Disagree
a) … would be easy to use	□	□	□	□	□	□	□
b) … would be easy to learn	□	□	□	□	□	□	□
c) … would be easy to understand	□	□	□	□	□	□	□
d) … would be annoying	□	□	□	□	□	□	□
e) … would be distracting	□	□	□	□	□	□	□

The next two questions ask about a system that helps drivers avoid distraction by providing feedback ***after*** their drive. The feedback may take one or more forms, such as a percentage of time the driver may have been distracted, a map showing where the driver may have been distracted, or other measures of the driver's performance while driving.

3. Using the distraction warning system that provides feedback about distracted driving after my drive…

	Strongly Agree	Agree	Slightly Agree	Neutral	Slightly Disagree	Disagree	Strongly Disagree
a) … would make me a safer driver	□	□	□	□	□	□	□
b) … would make it easier to drive	□	□	□	□	□	□	□
c) … would make me more aware of the driving situation (other vehicles, lane position, etc.)	□	□	□	□	□	□	□
d) … would reduce speeding events	□	□	□	□	□	□	□
e) … would reduce distractions	□	□	□	□	□	□	□
f) … would reduce lane departures	□	□	□	□	□	□	□
g) … would improve my driving	□	□	□	□	□	□	□

4. The distraction warning system that provides feedback about distracted driving after my drive …

	Strongly Agree	Agree	Slightly Agree	Neutral	Slightly Disagree	Disagree	Strongly Disagree
a) … would be easy to use	□	□	□	□	□	□	□
b) … would be easy to learn	□	□	□	□	□	□	□
c) … would be easy to understand	□	□	□	□	□	□	□
d) … would be annoying	□	□	□	□	□	□	□
e) … would be distracting	□	□	□	□	□	□	□

5. What is the maximum price you would pay for a system that redirected your attention to the roadway ***while*** you were driving? ____________

6. What is the maximum price you would pay for a system that provided feedback about your level of distraction ***after*** your drive? ____________

7. At the actual price of $300, how likely would you be to consider purchasing a system that redirected your attention to the roadway ***while*** you were driving? (Circle one)

Definitely would **not** consider		Might or might not consider		Definitely would consider
1	2	3	4	5

8. At the actual price of $300, how likely would you be to consider purchasing a system that provided feedback about your level of distraction ***after*** your drive? (Circle one)

Definitely would **not** consider		Might or might not consider		Definitely would consider
1	2	3	4	5

9. Would you consider purchasing a distraction warning system if you received an insurance discount? (Circle one)

Definitely would **not** consider		Might or might not consider		Definitely would consider
1	2	3	4	5

10. Would you use a distraction warning system if it came standard on your vehicle? (Circle one)

Definitely would **not** consider		Might or might not consider		Definitely would consider
1	2	3	4	5

3. What is the maximum price you would pay for a distraction warning system like the one you used during your study drive? ____________

4. At the actual price of $300, how likely would you be to consider purchasing a distraction warning system like the one you used during your study drive? (Circle one)

Definitely would **not** consider		Might or might not consider		Definitely would consider
1	2	3	4	5

5. Would you consider purchasing a distraction warning system if you received an insurance discount? (Circle one)

Definitely would **not** consider		Might or might not consider		Definitely would consider
1	2	3	4	5

6. Would you use a distraction warning system if it came standard on your vehicle? (Circle one)

Definitely would **not** consider		Might or might not consider		Definitely would consider
1	2	3	4	5

Appendix T: Distraction Mitigation Training Presentation

Pre-Drive Information for Study Participants

Feedback Concepts and Distracted Driving

Please press the space bar or use the
↓↑ keys to advance to a new slide.

Instructions

Each slide will play on its own. Listen to each slide then go to the next slide when you are ready. You may ask questions at any time or at the end.

Purpose of the Study

The goal of this study is to evaluate feedback concepts related to distraction and driving.

You will engage in tasks that mimic activities people often do while driving, such as reaching into the backseat or adjusting the radio.

You may receive different types of feedback based on your performance during the drives.

Getting Ready

The next few slides go through the procedures for entering the simulator and preparing for your drive.

Interior

Seat Adjustments

Steering Wheel Adjustments

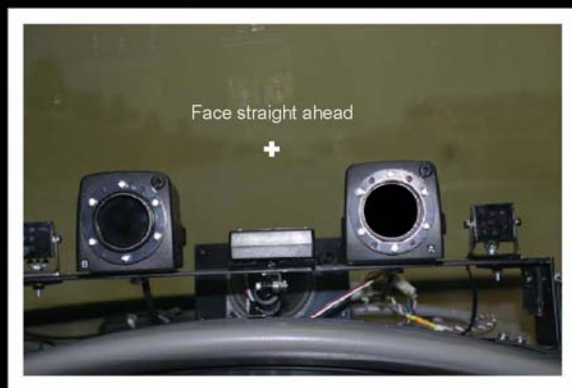
Simulator Safety

Once the adjustments to your driving position have been made, please fasten your seatbelt.

Do not unfasten your seatbelt or open the car door until you are instructed to do so.

During the time that you are not driving, we ask that you sit in the "resting position," with your hands off the steering wheel and your feet pulled back and away from the pedals.

Eye Tracking



Getting Comfortable in the Car

You may adjust the mirrors by using the control panel on the door. Set the side mirrors in much the same way as you would set the mirrors on your car. Wait to adjust the mirrors until after the eye tracking cameras have been calibrated. The control panel should be pressed firmly. If you need assistance, please ask the researcher in the simulator for help.

Intercom System

The car has an intercom system which allows the researchers to hear you. It is already adjusted for the drive today. If for any reason you want to stop driving, please tell us. The operator will hear you and can end the drive in just a few seconds.

Practice Drive

The drive starts with your car parked on an urban road. When told to begin, press on the brake, shift into drive, and begin to drive.

This drive is designed to help you get used to the simulator and allow you to practice the tasks that will be presented during your drives.

Navigation instructions will guide you through your route and a recording will tell you when it is time to stop.

Study Drives

After your practice drive, you will complete two drives approximately 25 minutes in length. A series of three 5 minute drives will occur between the two longer drives.

The two longer drives start with your car parked on an urban road. You will drive through town, then enter a freeway, then exit onto a rural road. The short drives occur in each of these three environments.

Navigation instructions will guide you through your route and a recording will tell you when it is time to stop.

Click on the picture of the speaker to hear sample instructions.

Your Destination

Tasks during your drives

At several points during your drives you will engage in these tasks:
- Bug catching
- Arrow identification
- Flight information

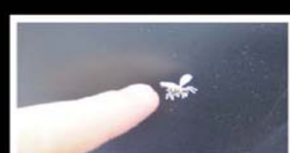
Throughout your drive you will also monitor the setting of the radio and adjust it back to a specific level.

The goal is to complete as many tasks as quickly as possible, while driving safely.

The following slides describe each of these tasks in more detail. You will have a chance to practice all tasks in the simulator before and during your practice drive.

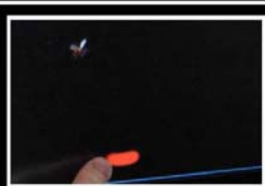
Bug Catching Task

When you hear buzzing, a virtual bug will appear on a touch screen located behind the passenger seat. Follow the bug by placing your finger on the touch screen where the bug is located. You must keep your finger on the screen and follow the path of the bug by tracing its path until you no longer hear it buzzing. The buzzing will get more intense until you begin the task.



k the picture of the speaker to hear the buzzing.

Task2: Bug Catching Task



You will see a RED glow around your finger if you are not doing a good job tracing the path of the bug.

You will see a GREEN glow around your finger if you are doing a good job tracing the path of the bug.

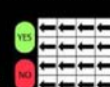
Your goal in this task is to maintain a green glow until you catch the bug. The buzz noise will stop when the task is complete.

Arrow Identification Task

This task asks you to identify when an "up" arrow is presented in a set of matrices. You will hear a prompt telling you to begin the task. The prompt will play until you begin the task. Click the picture of the speaker to hear the prompt.

After you hear the prompt, press "Start" on the display located to your right in the center console. A matrix of arrows will appear on the display. Look at the display and decide if an "up" arrow ⬆ is one of the arrows.

If there is an "up" arrow then press "yes".
If there is *not* an "up" arrow then press "no".



After you select your answer, a chime will play when the next matrix appears. Click the picture of the speaker to hear the prompt.

Your goal is to get as many correct answers as possible.

Flight Information Task

For this task, you will need to determine whether the flight will arrive on time or be delayed. You will hear a prompt telling you to check flight information for a flight you are meeting at the airport. The prompt will play until you begin the task. Click the picture of the speaker to hear the prompt.

You should respond to the prompt by saying “check flight”. Then you will hear information about a flight.

You will use a voice-activated system to call the airline and navigate through an information menu by answering questions about your flight. After answering the questions, you will be given complete flight information. Using this information you will verbally report whether the flight will arrive on time or be delayed.

The next slide will show an example of the information menu.

Flight Information Task - Example

Practice by saying the example responses out loud after the prompts.

Prompt: “Check Flight Information.”
You say: “Check flight.”
System: “Delta flight 435 departing at 2:15 PM from Chicago”
You say: “Call [name of airline]” for this example *“Call Delta”*
System: “Flight number even or odd?”
You say: “even” or “odd” for this example *“odd”*
System: “Flight time of day?”
You say: “AM” or “PM” for this example *“PM”*
System: “Departure city?”
You say: the city name, for this example *“Chicago”*
System: “Flight scheduled to arrive in St Louis 3:20 PM arriving at 3:40 PM.”
You say: “on time” or “delayed”, for this example *“delayed”*

Your goal is to correctly state the flight status. A wrong answer to one of the questions may mean the system will not be able to identify your flight arrival information.

Radio Setting Task

Throughout your drive you will also monitor the setting of the radio. The setting will start at "50" and will drift from time to time accompanied by increasing volume of static as it drifts.

When you notice the setting has drifted, you should adjust the setting back to "50" using the buttons on the display.

Rating Workload

At several points during your drives, you will be asked to rate how difficult you found maintaining your speed, staying in your lane and your workload during each of the tasks and at other times during the drive. Workload refers to how demanding you found the task. Using the stylist, you will press the colored button then make a slash across the line for that task.

You will have a chance to practice in the car.

Here's an example:
Please rate the workload you experienced during each of the following:

Rating task and driving performance

At three points in your first and last drives, you will be asked questions about the tasks, your driving performance, and your thoughts about peer drivers' performance.

To complete the surveys, you will need to know what we mean when we say "task" and "peer driver".

One **task** equals:

- A series of arrows matrices, OR
- Tracking the bug two times with a break of a few seconds between its buzzing, OR
- One flight information voice menu

A **peer driver** refers to someone of the same age, gender, occupation, or driving experience. Assume this peer is completing the same study procedures as you are.

Feedback

You will receive feedback based on your performance during your study drives.

One type of feedback relates to your task performance. You will receive a score between 0 and 100, with higher numbers indicating better task performance. This score is based on:

- How quickly you begin the task after the prompt
- Whether you continuously attend to the task once you have started
- Whether you perform the tasks correctly

Other types of feedback may also be presented.

Remember, the goal is to complete as many tasks as quickly as possible, while driving safely.

Summary

- You will drive in a simulated vehicle as you would normally drive in the real world.
- At times during the drive, you will engage in some tasks that mimic various behaviors drivers sometimes do.
- Three times during each long drive you will rate how difficult you found the tasks and rate your performance and that of your peers.
- You will receive feedback while in the simulator, including scores on your task performance.
- You will complete surveys about how you feel after three of your drives. Other surveys will be completed after your drives.

Conclusion

This concludes the briefing presentation. We can answer any questions you may have at this time.

Appendix U: Distraction Mitigation Debriefing Statement

Thank you so much for participating in this study. Your participation was very valuable to us.

In this study, we were interested in gathering driving and questionnaire data comparing the effect of different feedback concepts on reducing distracted driving. In the training presentation we noted that you would receive feedback based on your performance during the study drives. We told you how task performance was calculated, but we did not provide detail about other forms of feedback you may experience during your drives. In addition to feedback about your task performance, some of you received feedback meant to reduce your level of distraction. You either received feedback while you were driving, after your drive, or you received no feedback related to your level of distraction. We needed to keep secret the mitigation approaches and your assignment to a group that may or may not receive a mitigation in order to minimize any changes in participants' behavior based on assumptions that levels of distraction should change between drives.

For participants who received feedback after their drive, peer data was presented along with your distracted driving data. The peer data comes from a combination of non-distracted and distracted drives collected during an earlier study that used a similar protocol to the one used today. To determine peers' levels of distraction and distracted driving performance, we more heavily weighted the non-distracted drive data in order to reflect a driving population where the majority of drivers were not distracted. Peer distracted driving data does not reflect real-world peer data.

Because one of the primary ways we are evaluating the success of the feedback concepts is whether or not you chose to defer initiating a task, it is important that you not discuss strategies for delaying or diverting the tasks with anyone else until the study is complete. Our efforts will be greatly compromised if participants come into the study knowing ways to avoid the tasks. To this end, we would ask that you not discuss any of the details of the study until March 1, 2011.

Appendix V: Detecting Distraction and Degraded Performance With Visual-Motor Coordination Metrics

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CHAPTER 1. DISTRACTION AND VISUAL-MOTOR COORDINATION

According to the Fatality Analysis Reporting System (FARS, 2008) of the National Highway Traffic Safety Administration, the fatality rate per 100 million vehicle miles decreased by 17 percent from 2000 to 2008 (1.53 and 1.27, respectively). These statistics suggest that driving is becoming safer, likely reflecting a combination of changes in driver behavior as well as road and vehicle design (SafetyNet, 2009). In-vehicle information systems (IVIS) and advanced driver assistance systems (ADAS) are intended to enhance safety and mobility, and the reduction in fatalities partially reflects these advances.

However, rapid development of in-vehicle technology and mobile electronic devices threatens to undermine such improvements. These systems could place demands on drivers that might lead to distraction and a diminished capacity to perform driving tasks (Hoedemaeker & Neerincx, 2007). Fatal crashes with reported driver distraction increased from 10 percent to 16 percent during the period from 2005 to 2009 (NHTSA, 2010). Moreover, driving is becoming more demanding due to increasing traffic density: the number of licensed drivers in the United States increased from 190.6 million in 2000 to 208.3 million in 2008 (FARS, 2008). These trends suggest that driver distraction detection and mitigation could help maintain safety by alerting inattentive drivers to demanding driving situations.

Driving is a complex and demanding task, but it is not perceived as such by drivers who often shift their attention between driving and non-driving tasks (Young & Regan, 2007). Such intermittent attention to the road can undermine driving safety, but drivers often adapt their behavior to the environment by making decisions as to when to perform the secondary task without compromising driving performance (Poysti et al., 2005). To complete the secondary task successfully and to maintain safe driving, drivers often compensate for decreased attention to driving by increasing their safety envelope, i.e., reducing speed and maintaining larger headways (Horberry et al., 2006). However, this compensatory strategy is not always successful. Drivers fail to fully compensate for their inattention to driving because they often underestimate the risks involved in performing particular secondary tasks (Strayer & Johnston, 2001; Lesch & Hancock, 2004; Horrey et al., 2008). In these cases, drivers fail to adequately divide their attention between driving and secondary tasks. This excessive or poorly timed diversion of attention from driving can challenge driving performance and increase the crash risk.

The contribution of such poorly timed diversions of attention make substantial contributions to crash likelihood. An analysis of the naturalistic driving data from 100 instrumented vehicles (100-car study) found that driver inattention contributed to 78 percent of crashes and 65 percent of near-crashes (Klauer et al., 2006). In this study, driver inattention included “secondary task engagement,” “driving related inattention to the forward roadway,” “non-specific eye glance away from the forward roadway,” and “drowsiness.” Distraction caused by secondary tasks associated with off-road glances was the most frequent type of inattention observed in this study, contributing to approximately 43 percent of crashes and 27 percent of near-crashes. This suggests that the risk of crash while performing secondary tasks is higher than the risk while driving without any secondary tasks.

The type of distraction affects the likelihood of crashing. Complex secondary tasks, such as dialing a cell phone or reading, increased the likelihood of crashes/near-crashes by three times, producing an odds ratio (OR) of 3.10 (confidence interval (CI): 1.72, 5.47). Moderately complex tasks, such as inserting/retrieving CDs or eating, increased the crash likelihood by 2.1 (CI: 1.62, 2.72). Klauer et al. (2006) defined task complexity as the number of glances away from the road and the number of button presses. In general, glances totaling more than two seconds for any purpose increased near-crash/crash risk to double that of normal baseline driving. This result indicates that safe driving can be directly related to a driver glance pattern – the combination of off-road and on-road glances.

Secondary task performance changes drivers' glance patterns even when the task does not require the driver to look away from the road (Harbluk et al., 2007). Gaze concentration, i.e., percent road center (PRC), was found to be highly sensitive to the demands of visual and cognitive in-vehicle tasks. Gaze concentration decreases with visual task difficulty and increases with cognitive task difficulty (Victor et al., 2005). Moreover, the changes in driver glance pattern can identify the intention to engage in non-driving activities: eye movements in advance of attention shifts are motivated by the action preparation and preliminary perception of objects and events (Land, 2006).

Based on the effect of the secondary task on driver performance, two types of distraction – visual and cognitive – were distinguished (Victor, 2005). Visual distraction associated with glances away from the road leads to lapses in vehicle control. Cognitive distraction associated with allocation of glances to the road center leads to more precise vehicle control compared with driving while visually distracted but diminishes the driver's perception of the broader driving situation. Both cognitive and visual distractions are revealed through eye movements.

Detecting Driver Distraction

Technology that can detect and mitigate distraction could play a central role in maintaining safety. Systems with real-time distraction assessment monitor and continuously evaluate a driver's level of distraction according to predetermined criteria. Once criterion specified levels of distraction are detected, the system could provide feedback to drivers that might help them better assess the situation and improve driving performance, or it could be combined with active safety systems that take over vehicle control when distraction is detected. Concurrent feedback to guide immediate improvement or retrospective feedback after the trip to induce long-term behavioral changes has been shown to help drivers modulate distracting activities (Donmez et al., 2007; Donmez et al., 2008). However, the greatest benefit may be from real-time detection of diminished driver performance in advance of crash imminent conditions associated with inattention.

Correctly identifying driver distraction in real time is a critical challenge in developing these distraction mitigation systems, and this function has not been well developed. The difference in visual behavior and driving performance associated with different types of distraction requires different sets of sensors and algorithms to detect distraction (Liang, 2009). The algorithms for distraction detection primarily are based either on eye measures or on driver performance measures (e.g., speed, lane position, and steering); the relationship between these two types of measures is not established. The combination of different approaches, e.g., coupling the distraction detection algorithms based on different metrics, such as eye glance and vehicle data, could increase sensitivity of the system and safety benefit framework to detect different types of distraction. Metrics Used to Detect Distraction

Numerous studies have examined different types of assessment metrics and algorithms that could be sensitive to distraction. These include metrics associated with vehicle control, vehicle state, and driver behavior (see Part I, Chapter 2). Drivers react to changes in the roadway situation by modulating the lateral and longitudinal controls: steering wheel, brake pedal, and accelerator pedal. Distraction can interfere with driver perception and response, leading to possible changes in the time and magnitude of the driver's reaction to stimuli, including how the driver interacts with surrounding traffic. Likewise, eye glance and gaze patterns vary as drivers engage in different types of secondary tasks. Each produces distinctive signatures of distraction.

Steering is an important metric of vehicle control because of its potential as a timely indicator of distraction. Steering wheel changes have been shown to increase for both visual and cognitive distractions in comparison with normal (non-distracted) driving but in different ways: a visual secondary task leads to increased steering wheel movements in a wide range of amplitudes (i.e., 2-6 degrees), whereas cognitive tasks cause corrective movements with small amplitudes (less than 1 degree) (Östlund et al., 2006). Assuming undistracted drivers apply smooth steering adjustments, steering entropy might measure the predictability of abrupt steering wheel movements associated with distraction (Nakayama et al., 1999). The higher the entropy, the greater mismatch between the predicted steering wheel position associated with a smooth response and abrupt inputs has been shown to be sensitive to both visual and cognitive distraction: involvement in a secondary task increased entropy.

Generally, lateral control degrades with increasing levels of visual distraction, but it becomes more precise under cognitive distraction (Engstrom et al., 2005; Östlund et al., 2006). This implies that involvement in visual tasks can lead to a more degraded driving performance compared with cognitive distraction. Distractions also influence speed and headway maintenance. Östlund et al. (2006) found visual distraction leads to decreased speed, but cognitive distraction did not influence speed significantly. Similar to speed, headways increased under visual distraction and maintained relatively unchanged with cognitive distraction (Östlund et al., 2004). On the other hand, the speed variations with tendency to decrease were found in numerous studies with hands free and handheld cell phones (Patten et al., 2004; Rakauskas et al., 2004). These changes in speed and headway were attributed to the driver's compensatory behavior to manage the increased attentional demands.

Eye movement metrics such as glance duration, frequency, position (horizontal and vertical), and type (on-road and off-road), were found to be sensitive to the demands of driving and secondary tasks. Changes in glance pattern measured through these metrics can indicate presence of distraction. Moreover, the glance pattern while performing cognitive tasks is different from visual tasks. The frequent and/or long off-road glances indicate visual distraction and concentrated glances toward the road center indicate cognitive distraction (Victor et al., 2005). Distracted drivers check the mirrors and the speedometer much less frequently while performing secondary cognitive and verbal tasks relative to no task conditions and spend more time looking to the center of the road (Recarte & Nunes, 2000; Harbluk et al., 2002). This gaze concentration was reflected in reduced horizontal and vertical variability of gaze positioning as well as longer duration of on-road glances.

In summary, visual and driver performance metrics can be used for distraction detection (Table 5). Types of distraction can be differentiated based on differences in visual behavior and driving behavior, but changes in behavior associated with cognitive distraction are less dramatic than those associated with visual distraction.

Table 5 Summary of distraction assessment through visual and driver performance metrics

	Visual distraction: *“eyes-off-road”*	Cognitive distraction: *“mind-off-road”*
Vehicle control	abrupt steering movements with large (2-6 degrees) amplitude; large steering entropy	corrective movements with small (less than 1degree) amplitude; small steering entropy
Vehicle state	large and frequent lane deviations; speed decrease and headway increase	unchanged or small lane variation; speed does not change significantly
Visual behavior	frequent and long off-road glances	visual attention allocated to the road center

Algorithms diagnostic of Driver Distraction

Visual and cognitive distractions are fundamentally different and different algorithms are required to predict degradations in driver performance associated with each type of distraction. The combination of different glance behavior metrics has been considered in predictive models for the risks associated with visual distraction. Cognitive distraction identification is a more complex process than visual distraction because the mechanisms involved in cognitive impairment have not been precisely described.

Algorithms focused on visual distraction have considered many parameters that might contribute to increased crash risk. Engström and Mårdh (2007) developed an algorithm that combined duration, history, and eccentricity of off-road glances to estimate the total visual demands of a task. The visual demands were described as the summation of the product of the 1.5^{th} power of duration with a penalty for eccentricity of the glance relative to the road center for each off-road glance. 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 et al., 2007).

Another approach of integrating the effect of glances over time is to define a buffer that reflects drivers’ capacity to respond (Kircher et al., 2009). The algorithm integrates three types of glances over time: on-road when drivers glance toward the “field relevant for driving” (FRD), driving related (e.g., mirrors or speedometer), and off-road glances. The level of the buffer increases during on-road glances and decreases during glances away from the road in a linear manner. During latency phase of 0.1 sec for the transition from off-road to FRD glances and 1 sec for transition from on-driving to FRD glances, the buffer level remains at the current position before increasing. Maximal buffer is two seconds, and when the buffer goes to zero, the driver is considered distracted.

Cognitive distraction degrades longitudinal control and hazard perception, but is less risky, less consistent, and more difficult to identify compared to visual distraction. Several methods have successfully differentiated between visual and cognitive distraction. The combination of glance duration and frequency in Percent Road Centre (PRC) or Total Glance Duration (TGD) successfully differentiated between visual and cognitive distraction; PRC increased with cognitive tasks and decreased with visual tasks compared with normal driving (Victor, 2005).

Other methods integrate a number of eye movement measures (e.g., blink frequency, fixation duration, and pursuit measurements) and performance measures (e.g., steering wheel movements and lane position) summarized across a relatively long time interval. A decision tree technique was applied to estimate driver cognitive workload from eye glances and driving performance measures (Zhang et al., 2004). Support Vector Machines (SVMs) and Bayesian Networks (BNs) successfully identified the presence of cognitive distraction from eye movements and driving performance (Kutila et al., 2007; Liang et al., 2007; Liang et al., 2007).

Perception-action Coordination in Driving

The perception-action control process plays a central role in driving (Regan et al., 2008). Information flow about the roadway and traffic situation guides a driver to control the vehicle. Interruptions of this information flow could cause diminished vehicle control and, as a result, lane keeping degradation. Different visual and driver performance metrics have been examined to detect distraction, but the relationship between them has not been established. The examination of the mechanism of action preparation based on visual information could reveal the relationship between eye movement and vehicle control. Changes in this relationship could identify distraction.

In vision-guided tasks, including driving, the function of vision is to provide information to support action. Action preparation and execution are typically represented by three systems: gaze, motor, and visual (Figure 7). The gaze system locates and fixates task-relevant objects (e.g., bend, leading car, or stop sign); the motor system of the limbs carries out the task (e.g., steering, braking); and the visual system supplies information to those two systems (Land, 2009). Thus, the role of the visual system is crucial in this schema: it reflects the scene of the world to provide information to the gaze and motor systems for action preparation and execution, respectively. .

Visual information from the outside world provides instruction to the neuromuscular control system through perception (path from visual to gaze and then to motor system in Figure 7). This coordination between perception and action can be observed in everyday activities such as driving, walking, reading, drawing, and playing ball games (Land, 2006). The eyes typically search for information about objects of interest to establish their locations and move to those objects about a second before each act initiation. People chose points for eye positioning before an action as the best for the spatial-temporal demands of the task (Land, 1993; Land & Tatler, 2001). This glance behavior is based mostly on the role of the objects in the task and not their salience. The eyes seldom move to objects that are irrelevant to the task. This coordinated attention-eye movement indicates the preparation for action (path from visual to gaze system on Figure 7).

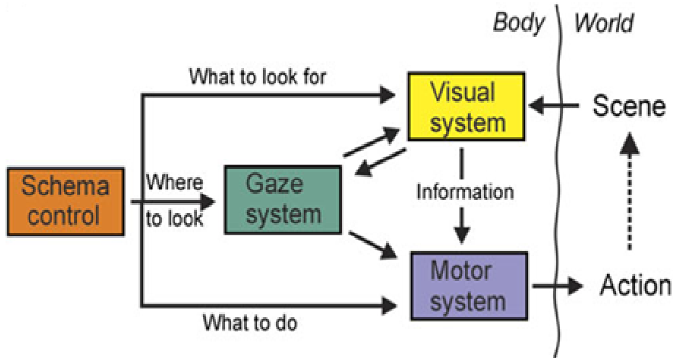


Figure 7 Relations of the schema, gaze, visual, and motor systems during the performance of a visually controlled action (Land, 2009).

In driving, visual information supports vehicle control. Specific eye movements observed in driving provide information about the roadway and traffic situation to control the vehicle. For example, for curve negotiation drivers fixated glance location on the tangent point of an approaching bend about 80 percent of the time to get the estimates of the bend's curvature (Land & Lee, 1994). The vanishing point was fixated on a straight road, and a point connected to the lead vehicle was a target point for the car-following task performance (Land & Horwood, 1995). The near-region fixation point provided information for lane keeping and monitoring vehicles and surrounding objects (Land & Horwood, 1995). These coordinated eye movements and vehicle control actions support safe driving. Changes in this coordination might lead to diminished vehicle control and to dangerous changes in vehicle state, such as lane departures.

The concept of eye-steering coordination also implies the eye movement itself contributes to the steering pattern. The coordinated eye and hand movements have been linked through the ocular control system, which feeds into the manual control mechanism to assist tracking (Miall & Reckess, 2002). When drivers were instructed to keep their gaze on the center of the screen while driving on the curvy road, they spent more time steering straight than they did in normal driving conditions (Marple-Horvat et al., 2005). The degree of coordination between horizontal eye movements and steering is highly consistent for both individual drivers and for different drivers travelling the same route (Chattington et al., 2007). The high covariation with eye movements (r =0.84) explained 71 percent of steering movements on the curvy road. Head movement explained a smaller percent of steering behavior – only 29 percent. These suggest that steering performance arises from eye movements, rather than from the acquired visual information, and the eye movements could be considered as an input to the steering controller.

Importantly, the correlation between eye and steering signals reflects driver impairment. The correlation was reduced when drivers were exposed to an attentional narrowing through high stress (Wilson et al., 2008). The horizontal eye movements were more focused in the central part of the road scene in the high-threat condition than in the low-threat condition while steering movements were not affected. The coordination between eye and steering movements is also lower during drunk driving. The most intoxicated drivers were the most affected in terms of their eye-steering coordination and experienced the most frequent and most serious crashes (Marple-Horvat et al., 2008). The time lead between eye and steering movements decreased from 710 ms to 402 ms with an increase of alcohol level from 0 mg/100ml to 35 mg/100ml.

These results indicate that (1) eye-steering coordination is highly consistent in natural driving on curvy roads; (2) eye movements precede steering; and (3) definition of a normal eye–steering coordination can help to identify impaired coordination that could be a result of different factors such as distraction, fatigue, and alcohol.

Based on these findings, a measure of coordination between eye and steering movements can help in driver state identification. However, state identification depends on the degree of correlation between eyes and steering signals for different eye movements. For instance, as discussed above, the degree of eye-steering correlation was very high on curvy roads for normal (non-distracted) driving: drivers moved eyes to guide steering. While driving on straight roads, drivers move their eyes less frequently to support their steering and this can cause weak correlation between two signals. Shifts from off-road to on-road glances might be associated with subsequent corrective steering movements. These coupled movements will be associated with lapses in vehicle control and can designate visual distraction.

Driving environment can also influence this correlation. Non-distracted driving in urban environment could cause weak correlation between eye movements and steering. The substantial visual information causes eye movements from the driving scene to different locations but does not require intensive steering movements. In this situation, the eye movements reflect glances to and away from the road to monitor pedestrians, intersections, and other hazards and do not guide steering. Thus, it is important to examine not only the changes in eye-steering correlation but also the causes of these changes.

Control Theoretic Models and System Identification to Describe Eye-Steering Coordination

The control-theoretic models of driving have been developed to predict driver-vehicle behavior. These models provide a formal structure to define a mathematical model of visuomotor coordination and the influence distraction might have on this coordination. Accurate description of driver behavior for normal (non-distracted) driving could be helpful in distraction prediction: changes in model parameters or changes in model fit could indicate distraction.

Early models of a driver as an adaptive controller were focused primarily on control-theoretic descriptions of steering control in lane keeping and curve negotiating tasks. These models had compensatory, pursuit, and precognitive control structures (McRuer et al., 1977; Donges, 1978). In compensatory behavior, the steering movement is a function of errors of vehicle position in the lane: the feedback of position error is an input into the vehicle control system. The pursuit control has a feed forward element: a driver has learned to compensate for the vehicle dynamics and can anticipate the desired path. The precognitive control assumes that a driver can generate steering movements based on previously learned control movements. The approach used in compensatory and pursuit control assumes that visual feedback is available for continuous error correction and path monitoring. i.e., this approach uses the *visual information-vehicle control* relationship. The examination of this relationship can help understand which visual information guides steering and how visual occlusion affects vehicle control. The following studies represent the attempts to answer these questions. Modeling the *visual information-vehicle control* relationship for normal driving conditions could elicit changes in this relationship caused by distraction.

Driver steering behavior with various degrees of occlusion was examined through two different modeling approaches (Hildreth et al., 2000). The first model assumed that drivers continually adjust steering to regulate the state of perceptual variables relevant to the task such as lateral position, heading, and their temporal derivatives. The second model considered continual steering toward the virtual target (similar to tangent point for the curve negotiation). Both models were considered reasonable for steering control. They reproduced the detailed shape of human steering profiles and similar degradation in performance with longer occlusion periods across the drivers. The target model, however, was found to be more intuitive because the relationship between target movement and the driver's response could be easily adapted to other steering tasks.

The concept of intermittency of visual information processing and steering control was applied in modeling of a predictive steering driver control (Roy et al., 2009). The intermittency of steering control was based on the assumption that the muscle torque increases gradually, and the wheel angle reaches the desired reference angle with a specific time lag associated with the human neuromuscular system. The model with intermittent control behavior closely mimicked driver steering control behavior. This approach showed that the intermittence period could vary with the driver workload or driving environment (e.g., road curvature). The eye-steering system defined for normal non-impaired driving on a specific type of road can differentiate driver impaired state (high workload, fatigue, or distraction) when data from the impaired state is used. This variation of information processing time could assume that the parameters of the model will change with driver state indicating driver high workload or distraction.

Another attempt of modeling driver steering behavior based on visual information was done through considering perception-action aspects of driving task performance. An integrated driver model developed in the ACT-R (Adaptive Control of Thought-Rational) cognitive architecture is focused on the processes of control, monitoring, and decision making for driving tasks (Salvucci, 2006). The cognitive architecture is based on chunks of declarative knowledge and condition-action production rules that operate on these chunks. The model control component linked perceptual variables (the visual cues of the environment perception) to vehicle control actions – steering, acceleration, and braking. The control law for steering angle φ was expressed through a steady far point $\Delta\theta_{far}$, near point $\Delta\theta_{near}$, and near point at the center of the lane θ_{near}

Equation 1

$$\Delta\varphi = k_{far}\Delta\theta_{far} + k_{near}\Delta\theta_{near} + k_I\Delta\theta_{near}\Delta t$$

As with the models discussed above, this model defines the relationship between driver performance and continuous visual information. Interruptions in visual information could cause changes in the model performance.

All these efforts to model the driver-vehicle system address the goal of predicting driver performance based on visual behavior. Such models might support distraction prediction in two ways. Distraction-related disruptions in visual information could lead to changes in model performance. Such changes could also lead to other models providing a better fit to the data. Both outcomes could indicate distraction.

The control theory method of system identification offers promising methods for identifying an eye-steering system (Table 6). System identification is a method to obtain the characteristics of a mathematical model of a system using experimental data and to create an input-output map (Ljung, 2009). Different parametric models that can describe a system in terms of differential equations and transfer functions could be generalized by linear polynomial model shown in Equation 2.

Equation 2

$$A(q)y(t) = G(q)u(t) + H(q)e(t)$$

and

$$G(q) = \frac{B(q)}{F(q)} \quad \text{and} \quad H(q) = \frac{C(q)}{D(q)}$$

where $u(t)$ and $y(t)$ are the input and output of the system respectively; $e(t)$ is zero-mean white noise, or the disturbance of the system. A(q), B(q), C(q), D(q), F(q) are polynomials that contain the time-shift operator q, and $G(q)$ and $H(q)$ are transfer functions of the deterministic and stochastic parts of the system respectively (Figure 8).

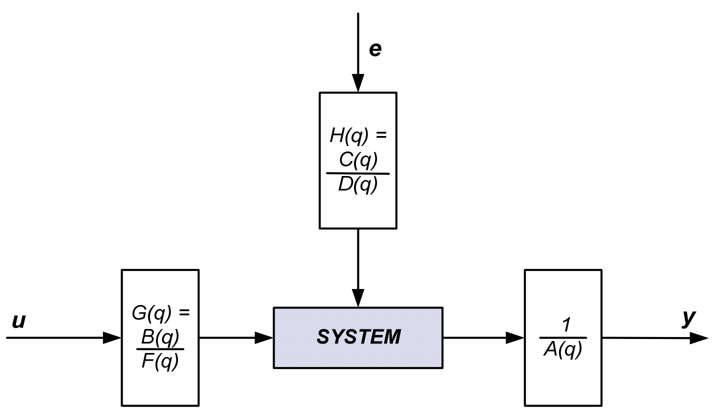


Figure 8 General linear model structure.

To predict steering angle current value from its past values, autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) can be considered. When the observed time series is driven by some "forcing" signal (i.e., eye movements predict steering), ARX and ARMAX model structures with an "exogenous" variable should be considered.

Table 6 Summary of models' structure

Model structure	Polynomials	Description
AR: $A(q)\,y(t) = e(t)$	B(q), C(q), D(q), and F(q)=1	This structure is for time series analyses. There are no inputs or disturbances in the model; current output dependent only on previous outputs.
ARMA: $A(q)\,y(t) = C(q)e(t)$	B(q), D(q), and F(q)=1	This structure is for time series analyses. This model is for a single-output time series and modeled disturbances. There are no inputs.
ARX: $A(q)\,y(t) = B(q)\,u(t-n_k) + e(t)$	C(q), D(q), and F(q)=1	This is the simplest model incorporating the stimulus signal. This structure is preferable for high order models. The disturbances are part of the system dynamics.
ARMAX: $A(q)\,y(t) = B(q)u(t-n_k) + C(q)\,e(t)$	D(q), and F(q)=1	The structure includes modeled disturbance dynamics that makes models more flexible in handling disturbances than the ARX structure.

Table 6 Summary of models' structure (Continued)

Model structure	Polynomials	Description
Box-Jenkins (BJ): y(t) = [B(q)/F(q)] u(t-n_k) + [C(q)/D(q)] e(t)	A(q)=1	This structure models disturbance separate from system dynamics. The model is useful when disturbances enter late in the process.
OE (output-error): y(t) = [B(q)/F(q)] u(t- n_k) + e(t)	A(q), C(q), D(q), and F(q)=1	This structure is common for dynamical systems. It is useful for dynamics parameterization, but not for noise estimation.

ARIMA Model

ARIMA model is made up of two parts: (1) the autoregressive (AR) that describes the dependence of the current time series value on the previous values; and (2) the moving average (MA), a weighted sum of the previous points of the noise series. The integrated part (I) of the model refers to the stationary assumption. For the stationary time series data, the ARMA without the integrated part is shown in Equation 3.

Equation 3

$$y_t = \underbrace{a_1 y_{t-1} \ldots + a_p y_{t-p}}_{\text{AR model of } p \text{ order}} + \underbrace{e_t + b_1 e_{t-1} \ldots + b_q e_{t-q}}_{\text{MA model of } q \text{ order}}$$

ARX and ARMAX models

In the dynamic system the output (*endogenous* variable) can be described not only as a linear function of a current value of the input (*exogenous* variable) but also as a function of previous values of both the input and output, shown in Equation 4, measured at times *t*, *t-1*, *t-2*, etc.

Equation 4

$$y(t) + a_1 y(t-1) + \cdots + a_{n_a} y(t-n_a) = b_1 u(t-n_k) + \cdots + b_{n_b} u(t-n_k-n_b+1) + e(t)$$

where n_a, the number of previous outputs that affect the current output $y(t)$, and n_b, the number of previous inputs that affect the current output $y(t)$, are the orders of the model, n_k is the number of input samples that occur before the input affects the output (time delay or dead time), and $e(t)$ is white-noise. For example, the gaze direction (input) precedes steering wheel movements (output) by about 0.8 seconds (time delay in seconds) (Land 1997). In the eye-steering model, the number of input samples that occur before the input affects the output n_k is a product of sampling rate and time delay measured in seconds (it is assumed that n_b=1 and n_a=0).

This is the simplest ARX, AutoRegressive (related to output) with eXogenous input, model. This input-output relationship is presented for the single input-single output model (SISO); it could be extended for a multiple input- single output (MISO) case. In Equation 5, the symbolic representation of the ARX model is

Equation 5

$$A(q)y(t) = B(q)u(t - n_k) + e(t)$$

where q is the delay operator, $A(q) = 1 + a_1 q^{-1} + \cdots + a_{n_a} q^{-n_a}$, and

$$B(q) = 1 + b_1 q^{-1} + \cdots + b_{n_b} q^{-n_b+1}$$

The coefficient $\mathrm{B(q)/A(q)}$ is a transfer function that denotes the dynamic properties of the system, describing how the output is formed from the input. Disturbances at the output depend on noise source $e(t)$. The coefficient $1/\mathrm{A(q)}$ describes noise properties. Different sets of parameters of the mathematical model could describe different conditions of the system, e.g. distracted and non-distracted driving. This structure assumes that disturbances are part of the system dynamics and this type of model can be accepted when the disturbance of the system is white noise. If disturbances are not part of the system dynamics, the ARMAX structure will provide more flexibility for noise modeling through an additional term $(\mathrm{C(q)/A(q)})\, e(t)$ in Equation 5. Noise reflects the known and unknown influences on measured output that are not captured by the input. It explains the differences in output with the same input. There are many sources and causes of these disturbances $e(t)$: measurement noise, uncontrollable environmental effects, etc. The system identification problem is to define the coefficients in Equation 5.

Process Stationarity

These models are based on a steady state process (Ljung, 1987). The steady-state assumption implies invariance of several statistical properties of the signal, i.e., mean, variance, and autocorrelation do not change over the time of prediction. In general, time series can be represented as the following sum in Equation 6:

Equation 6

$$u(t) = trend + \ cycles + stationary \ \ stochastic\, process$$

where trend represents a general systematic linear or nonlinear component (i.e., mean) that changes over time; a cycles term relates to the seasonality and has a fixed frequency, phase, and amplitude; and stationary stochastic process is the part of time series that should be modeled (Gottman, 1981). The trend can be approximated by a linear function of $u(t) = a + bt + e(t)$, where $e(t)$ is a white noise with a constant variance and mean. The data with the nonlinear component need to be transformed – logarithmic, exponential, or polynomial functions – to remove the nonlinearity associated with variance changes. The cycle of the time series can be fitted with periodic function.

As a rule of thumb, non-stationary data cannot be modeled or forecasted accurately with approaches that assume stationarity. The data needs to be transformed into stationary data. There are two alternatives to eliminate trend of non-stationary data: detrending and differencing. Detrending is the operation of removing linear trend from the series by subtracting of the best-fit line from the data. Differencing transforms a time series by calculating the difference between two consecutive values of the series (Hartmann et al., 1980). Differencing operation can be applied n times to remove n^{th}-degree polynomial trend. Differencing does not remove the treatment effects (McCain & McCleary, 1979). This transformation simply gives a different representation of a time series model without affecting its parameters that represent intervention effect and describe systematic behavior of a model (Hartmann et al., 1980). Thus, removing a trend from the data focuses the analysis on the fluctuations in the data about the trend, i.e. stochastic process.

The tests that evaluate statistical independence of data and underlying trends are "run test" and "reverse arrangement test" that ensure the transformed data are stationary (Bendat & Piersol, 1986). The "run test" was applied to quantify the steadiness associated with the absence of a trend in baseline recordings of cardiovascular signals and to identify sub-periods of steady state during a sequence of physical activities (Castiglioni & Di Rienzo, 2004). The test was based on the runs defined as a sequence of identical observations coded by "+" or "–". These symbols designate if the signal value is greater or less than the median value. The hypothesis that the signal does not have a trend is associated with the independency of observations: the number of consecutive "+" and "–" is equal. The number of runs has a sampling distribution and this hypothesis can be tested at any desired level of (Bendat & Piersol, 1986). The mean and variance of the r (runs) distribution are $Mean[r] = N/2 + 1$ and $Var[r] = N(N-2)/4(N-1)$.

Reverse arrangement test was performed on the lateral position data to check the signal stationarity (Pilutti & Ulsoy, 1999). This test was based on counting the number of times that $x_i > x_j \; for \; i < j$. The number of reverse arrangements is a random variable with $Mean[ra] = N(N-1)/4$ and $Var[ra] = N(2N+5)(N-1)/72$. The total number of times (reversals) when the condition is satisfied for all x_i, when $i = 1,2, \dots N$ will have a sampling distribution and can be tested at any desired level of significance (Bendat & Piersol, 1986). The reverse arrangement test is considered more powerful than the run test for detecting monotonic trends in a sequence of observations, but not for detecting fluctuating trends (Bendat & Piersol, 1986).

On the other hand, there is an indication that the run test and reverse arrangement test are not always accurate tests for signal stationarity (Beck et al., 2006). This finding may reflect the fact that these tests were designed to determine whether or not a signal is random, rather than to ensure the signal is stationary (Siegel & Castellan, 1988).

A monotonic time series can be detected by plotting the data as a function of time and adding the best-fit line (Chambers et al., 1983). The nonzero slope of the best-fit line would be an indicator of a trend in the data. Another indication of the existence of linear or non-linear trend in the data is a nonzero value in a spectral density function at zero frequency (Gottman, 1981, p.47). Plotting the autocorrelation function as a function of lag can also reveal the presence of a trend in data: without trend, it will decay to zero much more rapidly than a linearly decreasing function. The detection of cycles in time series could be also done through the spectral and autocorrelation analyses: it will be the presence of thin spikes in the spectral density function and cycles in autocorrelation function.

Thus, for the eye-steering system identification using a black box modeling approach, the non-stationary data should be transformed into the trend-stationary ones. Information about trend and cycle in the time series is important and should be modeled before removal. Assuming that the segments with only one type of glance, i.e., on-road or off-road, is stationary, then the segments with two or more types of glances could cause changes in trend or cycle. The changes in autocorrelation function associated with glance pattern changes might be indicative of driver state, i.e., presence of distraction.

Driver State Assessment Through System Identification

Efforts in developing a mathematical model of human control performance in driving are based on the data from compensatory tracking tasks: subjects control a random input signal with the control devices (e.g., accelerator and steering wheel) to obtain a desired output (Smiley et al., 1980). The input-output system error (i.e., difference between the output and the input) prompts a driver to initiate a control and use it as a system input. For example, visual information from the driving scene could be used as a prompt of changes in vehicle state and the associated corrective steering movements. The interruptions in error tracking might lead to breakdowns in system performance. Thus, such models could trace changes in operator performance or behavior.

The following examples demonstrate the attempts of modeling system dynamics based on stationary signals to define driver state. A system identification approach was used to develop a model for driver state assessment with vehicle lateral position as an input and steering wheel position as an output (Pilutti & Ulsoy, 1999). A preliminary second order ARX model was created from desktop driving simulator data. It was shown that changes in the bandwidth and parameters (i.e., damping ratio, natural frequency, and gain) of such a model may indicate changes in driver state, i.e., normal driving vs. fatigued driving. The defined identification algorithm was applied to data from two-hour highway driving conducted in a full-vehicle driving simulator. The model parameters did not exhibit the trends expected as lane keeping performance deteriorates. Several reasons of not detecting driver impairment were: (1) the selected model structure was not the most appropriate; (2) the existence of nonlinear effects associated with a complacency zone when steering position remains constant while lane deviation errors build; (3) the choice of the low order model structure did not result in a good fit; and (4) the variations in parameters could cause poor differentiation between driver states. The last three reasons relate to model uncertainty.

An estimated model is always uncertain due to disturbances in the observed data and the lack of an absolutely correct model structure. Two types of uncertainty were considered in modeling lateral position through steering angle with a linear ARMAX structure: structured uncertainty related to the model parameters and unstructured uncertainty related to unmodeled dynamics (Chen & Ulsoy, 2001). In this study, the structured uncertainty was considered to represent the variation of driver behavior with time and the unstructured uncertainty was considered to represent model order and nonlinearity. It has been shown that the model order and nonlinearity associated with a complacency zone did not contribute to the unstructured uncertainty, but the variability in driver's steering behavior may be the primary source of the large uncertainty.

Both studies showed that the system identification approach could be used to detect driver impairment based on model parameter changes. Different model structures and orders should be examined for their best fit. A nonlinear relationship between input and output should be considered as a possible unstructured uncertainty when there is an intervention effect, i.e. changes in driver state caused by distracting activity. The changes in model fit could indicate changes in driver state, i.e., distraction.

Novel Distraction Detection Algorithms Using Eye-Steering Coordination

Previous research has demonstrated visual behavior (i.e., glance pattern) and driving performance (e.g., steering and lane keeping) reveals distraction. The prototypes and existing algorithms for distraction detection are mostly based on either eye measures or driver performance measures (e.g., speed, lane position, and steering). A prospective indicator of distraction based on combined eye and steering measures has yet to be considered.

The relationship between eye and driving performance metrics in the context of driver distraction has not been established. However, previous research considering control theoretic models of driver steering behavior suggest changes in the coordination between these metrics can indicate distraction and predict breakdowns in lane keeping. This consideration can also improve the sensitivity of the algorithm by differentiating the type of impairment (drowsiness vs. distraction) and robustness of the algorithm.

A relationship between driver visual behavior and vehicle control is expected because of observed eye-body coordination that is highly consistent in everyday activities – eye movements precede motor actions (Hollands et al., 2004). This coordination is very specific for different activities. The eye-steering coordination – Land's visual information framework – was observed in driving on open curvy roads (Land & Furneaux, 1997). The alternative (or additional) approach explains eye-steering movements through the oculomotor controller concept – movement centered framework (Wilson et al., 2008). This concept assumes that some neural centers produce and control eye movements and then assist the neural centers that control steering. Visual information intermittency in movement control assumes intermittent corrections – when each sub-movement is planned to reduce error developed in the previous step (Miall et al., 1988). These different concepts assume that the visual behavior and vehicle control relationship is strong enough to make a prediction about driver performance.

Based on these findings, the prediction of steering behavior could be done through the eye movements with the oculomotor controller as a transfer function. This prediction could be very valuable in crash risk assessment because changes in steering lead to changes in lane position with taking into account vehicle dynamics (Figure 9). This sequential *eye movement – steering –*

lane position behavioral model defined for non-distracted driving could predict large deviations from the centerline caused by visual distraction and false seemingly improved driving performance associated with cognitive distraction. In all the cases, the changes in driver performance could be caused by changes in eye-steering coordination that, in turn, could indicate driver state changes.

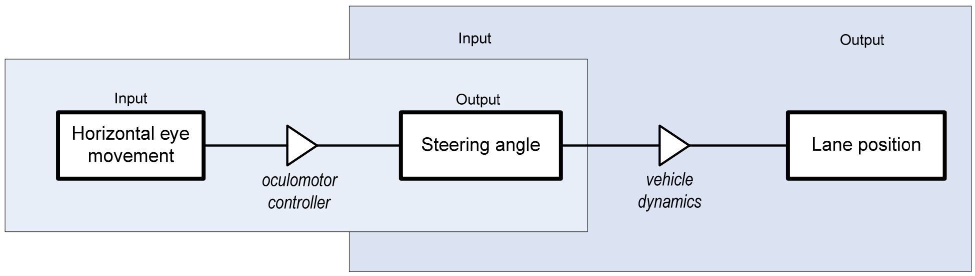


Figure 9 Eye movement – steering – lane position relationship.

This previous research suggests a novel approach to detecting distraction based on: (1) a model of steering wheel position as a function of its previous values and eye movement signal. This system can distinguish between distracted and non-distracted driving; and (2) eye-steering correlation changes can predict driver performance degradation. As a prospective indicator, it can mitigate and prevent crash risk caused by distraction. Here, the crash risk is associated with relatively large deviations from the centerline that can impact safety (Figure 10).

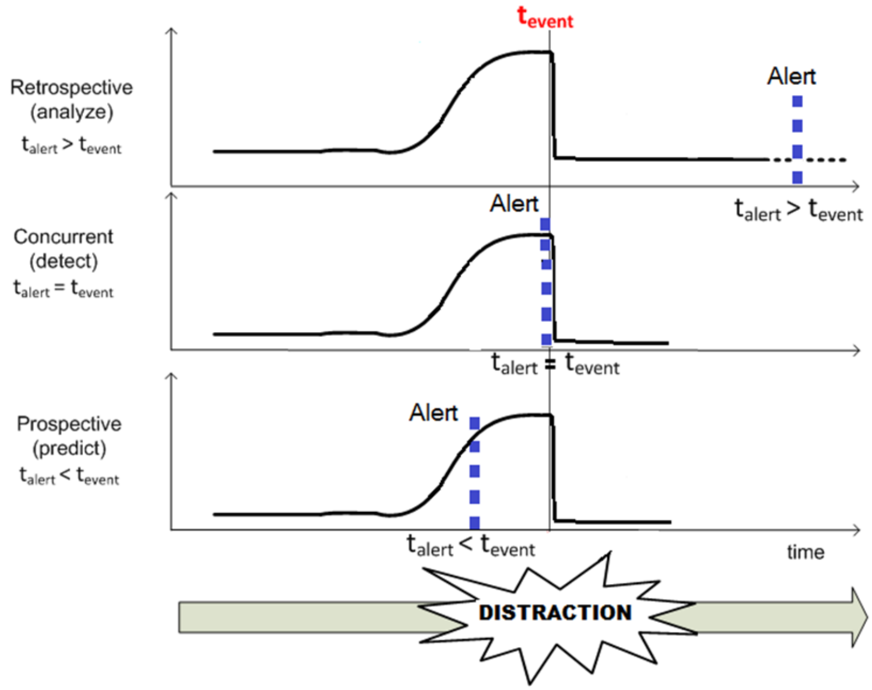


Figure 10 Comparison of the different timelines for distraction indication. Time of event is associated with the time of maximum risk of crash caused by distraction.

Objectives AND APPROACH

This research examines whether poor coordination between visual behavior and vehicle control can identify diminished attention to driving and predict breakdowns in lane keeping (Figure 9). It is hypothesized that (1) it is possible to detect distraction associated with off-road glances by considering relationship between visual and steering behavior and (2) the changes in eye-steering behavior prospectively indicate vehicle position in the lane and predict breakdowns in vehicle control, i.e., lane departures. This sequential *eye movement – steering – lane position* behavioral model is primarily based on eye movement type, i.e., on-road and off-road glances, and the changes in driver performance could be caused by changes in eye-steering coordination that, in turn, could indicate driver state changes. Figure 11 shows how distraction associated with off-road glances leads to changes in vehicle control (steering behavior) and lane keeping. Here, the off-road glances are associated with the visual task performance and are directed toward in-vehicle display. The center of in-vehicle display area is defined for visually and cognitively/visually distracted driving in the same manner: it reflects the most frequent fixations at the right side below the road center area.

Thus, detection of changes in eye-steering relationship associated with distraction could provide a prospective indication of risky changes in vehicle state, such as lane departures.

This report develops control-theoretic techniques to identify driver impairment by combining eye movement and driver performance metrics. In the context of distraction-related impairment, this objective is achieved through two analyses:

<u>Analysis 1: Eye-Steering System identification:</u> This analysis distinguishes between distracted and non-distracted driving using a control-theoretic approach of eye-steering system

identification. Using existing data, this approach defines a mathematical model of the eye-steering system based on measured input (eye position) and output (steering angle) data from a baseline (non-distracted) condition. Then using data from a distracted condition as an input, the model performance, i.e., the difference between predicted by the model and measured output, should change to reflect distraction. This section will examine the capability of the model to fit two kinds of secondary behaviors and driver performance behavior

Analysis 2: Prospective indicators of control breakdowns: This analysis examines whether eye-steering model predicts breakdowns in vehicle state (lane departures). To examine this assumption, different measures of model performance are tested on their sensitivity to lane departures.

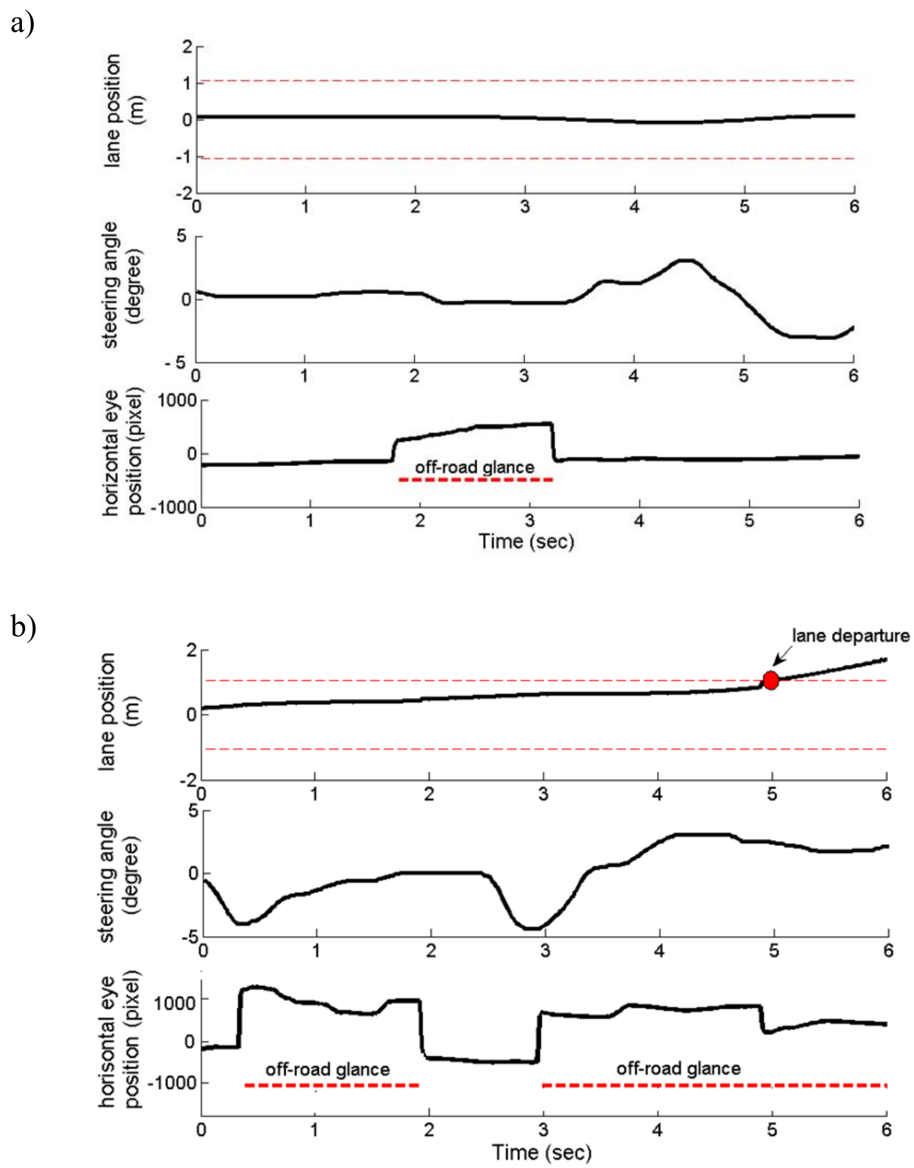


Figure 11 The sample of eye movements, steering responses, and lane position time series for (a) non-distracted and (b) distracted driving

CHAPTER 2. APPLICATION OF SYSTEM IDENTIFICATION TECHNIQUES TO DETECT DRIVER DISTRACTION

A system identification approach is used to construct mathematical models of the eye-steering system from input-output data. This black-box modeling approach fits linear and nonlinear models to data. The fit of the models to the data and the values of model parameters might be useful indicators of distraction and might also differentiate types of distraction.

Dataset AND Distraction Tasks

For this study, data from a simulator study of Liang (2009) is used. 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. Eye movement (eye position) and steering movement (steering angle) signals from 16 participants (8 male and 8 female) 35 to 55 years old were collected while the participants drove on a straight, five-lane suburban arterial roadway comprised of two lanes in each direction separated by a center turning lane. Both a faceLab eye tracking system by Seeing Machines (version 4.1) and the simulator collected data at 60 Hz. Participants performed 8-minute drives for each non-distracted (baseline) and distracted (visual/manual, cognitive, and combined cognitive/visual tasks) condition.

For the visual/manual distraction task (called visual task), the participants were instructed to match the direction of a given arrow within a 4x4 arrow matrix using a seven-inch LCD touch-screen interface located on the right side of the dash 25 degrees laterally and 20 degrees vertically below drivers' line of sight.

For the cognitive distraction task, the participants listened to an audio clip and identified which direction (e.g., east, north, and southwest) people faced based on the clip. The participants were instructed to speak out load the direction as soon as possible after hearing each turn and to press a button on the steering wheel at the same time. The task required auditory input, verbal and manual output, and spatial working memory.

For the combined cognitive/visual 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. 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.

Analysis Method

Parametric models are used to predict steering wheel angle through its previous values and eye movement location. This approach identifies a model that takes horizontal eye position as an input and generates steering angle as an output.

It is hypothesized that the model defined for the stationary data from non-distracted driving will result in different model fit values when data from distracted driving are used as an input into this model. If this hypothesis is confirmed, then model performance (measured through the *Best*

Fit value) as a driver state classifier can identify distracted driving. Model performance will be evaluated using a confusion matrix as well.

The results of the correlation analysis can be used to identify the model structure: the correlation within steering time series and between eye and steering time series allows prediction of a current value of steering signal through its previous values and eye position.

System Identification and Model Selection

The candidate models that can predict steering wheel position using only previous states of the steering output are ARIMA, ARMA, and AR time series modeling structures (Ljung, 2009). Models that predict steering wheel position using previous states of the steering output and current and previous states of the horizontal eye position input are ARX and ARMAX models (Table 6). An advantage of the models with moving average (MA) term has more flexibility in modeling disturbances than models without MA. The models with MA terms predict the current value of the series against previous white noise error terms or random shocks that propagate to future values of the time series. On the other hand, AR and ARX structures are simpler if the disturbances are a part of the system and could be represented as white noise. For the purpose of this study, the consideration of the ARX structure is more appropriate because (1) it combines two variables that represent driving and visual behavior; (2) it considers time delay between input and output that is indicative of distraction.

It was shown previously that vertical eye movement does not change significantly for different driver states (Wilson et al., 2008) and it was not correlated with steering movements (Wilson et al., 2007). Thus, horizontal eye position will be considered as the input to the steering controller.

Modeling should be done under the assumption that the signal is stationary (Ljung, 1987). The signal stationarity assumes that a mathematical model should be based on the process that is unchanged and stable during the time of prediction. This assumption implies that the mean, variance, and autocorrelation do not change over the time of prediction (Gottman, 1981). Thus, non-stationary data cannot be modeled or forecasted, it needs to be transformed into trend stationary data. However, eye movement non-stationarity could indicate changes in glance type and, consequently distracted driving. Therefore, all the segments of data should be tested for presence of trend. Before removing trend from the time series, i.e., subtracting the best-fit line in the least-squares sense from the data, it should be modeled. Removing a trend from the data focuses the analysis on the fluctuations in the data about the trend.

Model Estimation

The ARX model structure is defined by the three parameters n_a, n_b, and n_k from Equation 4. Guided by the correlation analysis, the time delay that corresponds to the x-value of a cross-correlation function maximum peak can be used for n_k selection. Nevertheless, the time delay and the optimal number of previous inputs n_b and previous outputs n_a terms will be defined by examining models with different sets of values and will be based on the model fit parameters.

The prediction error method (PEM) is applied to model parameter identification (Ljung, 1987), where a prediction error is defined as a sum of squares of differences between validation data output and one-step-ahead predicted output. The parameters of the model will be estimated and tested for statistical significance using the least squares method (as a special case of PEM) that minimizes the error term through determining $G(q) = \mathrm{B(q)/A(q)}$ and $\mathrm{H(q)} = 1/\mathrm{A(q)}$ parameters (see ARX structure in Table 6) as shown in Equation 7:

Equation 7

$$[G_n\ H_n] = \arg\min \sum_{t=1}^{n} e(t)^2$$

$$\text{where } e(t) = H^{-1}(q)[y(t) - G(q)u(t)]$$

The candidate models will be examined on the prediction error using the Akaike Information Criterion (AIC) or Akaike Final Prediction Error (FPE) as measures of model quality. Equation 8 shows that AIC and FPE are defined by the equations

Equation 8

$$FPE = V(\frac{1 + d/N}{1 - d/N})$$

and

$$AIC = \log V + \tfrac{2d}{N} = log(V(1 + \tfrac{2d}{N})) \approx \log FPE \text{ for d} << N$$

$$\text{where } V = \frac{1}{N}\sum_{t=1}^{N} e^2(t)$$

is the loss function, d is the number of estimated parameters, and N is the number of values in the estimation dataset.

The lower the prediction error value the better the model. The choice of AIC or FPE rather than R^2 is that even the adjusted R^2 value might lead to inclusion of additional model parameters and result in overfitting. Therefore, based on a high R^2 value, the best model will be the most complex one. Since the model simplicity is a critical aspect in model definition, the models will be compared with the information lost criteria, i.e., AIC or FPE, as a measure of both accuracy and complexity.

Model validation

The selected models (with the lowest order and prediction error) will be evaluated by (1) *Best Fit* value that compares simulated or predicted output with measured output; and (2) residuals' analyses.

In Equation 9, the *Best Fit* shows the percentage of the output that the model reproduces and computes as

Equation 9

$$Best\ Fit = [1 - \frac{|y - \hat{y}|}{|y - \mu|}]\ x\ 100$$

where y is the measured output, $\hat{y}$ is the simulated or predicted model output, and μ is the mean of y. The closer the value is to 100 percent the better the fit. When the value is 0 percent, the fit is no better than guessing the output to be a constant ($\hat{y} = \mu$). The *Best Fit* is a model performance function that is essentially the R^2 value. *Best Fit* could be negative indicating that the estimation algorithm failed to converge.

The model validation process includes an analysis of residuals. Residuals, as a difference between the predicted output from the model and the measured output, represent the portion of the validation data not explained by the model. The analysis of residuals assumes an examination of the residuals' auto-correlation and cross-correlation with the input (Ljung, 1987). The residual function of a good model should be white noise. This assumes that the noise signal should be a random function that is not correlated with itself. Based on Equation 10, the auto-correlation function of the residuals defined as

Equation 10

$$R_{ee}(k) = \frac{1}{n}\sum_{t=1}^{n} e(t-k)e(t)$$

should tend to 0 for any non-zero k and do not leave the confidence interval. The exceedence of the confidence interval could indicate that the model structure does not fully account for the data. Examination of system linearity could also be based on the tendency of normalized cross correlation function toward one. In the frequency domain, the coherence test is used to determine the presence of a linear relationship between input and output. The tendency of the coherence function to zero could be a result of one of the following conditions: (1) noise contaminates the measurements, (2) another input affects the output, and (3) the relationship between input and output is nonlinear.

The analysis of the cross-correlation function defined by Equation 11 between the residuals and the inputs evaluates if the model properly represents the relationship between signals:

Equation 11

$$R_{ue}(k) = \frac{1}{n}\sum_{t=1}^{n} u(t-k)e(t)$$

A cross-correlation function that exceeds the confidence interval suggests that the output is not properly described. The correlation between $u(t-k)$ and $e(t)$ for negative k, is an indicator of feedback in the model. A slowly varying cross correlation function outside the confidence region indicates an insufficient number of sampling intervals between the most and least delayed output. The presence of peaks is an indicator of a small number of sampling intervals between the most and least delayed input or wrong number of delayed samples between input and output (Ljung, 1995).

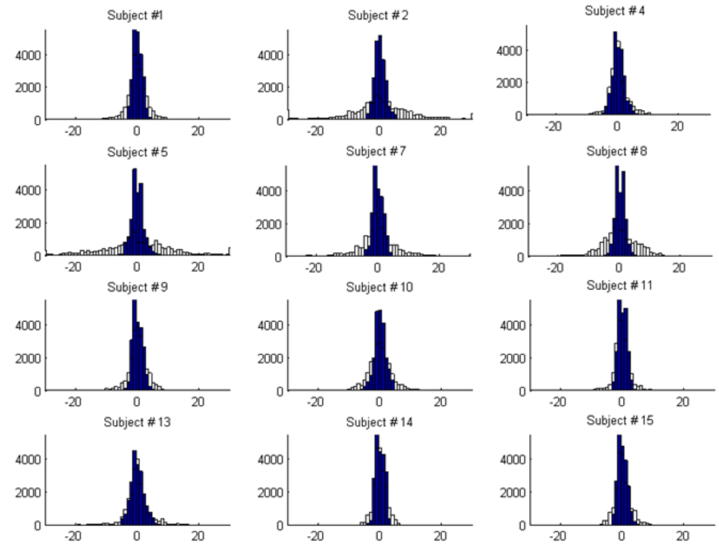
Thus, it is assumed that a good model should have (1) the residual autocorrelation function inside the confidence interval, indicating that the residuals are uncorrelated, i.e., normally distributed white noise (whiteness test); and (2) a cross-correlation function that lies inside the confidence interval, indicating that the residuals are uncorrelated with past inputs (independency test).

Driver State Differentiation Through Eye-Steering System Modeling

As a preliminary study, two different models were developed: One model was for non-distracted driving and the other model was for distracted driving. This allows a comparison changes in transfer functions associated with driver state. The black-box modeling approach, which defines a system without a priori information available, was used to define the relationship between eye signal as an input and steering signal as an output. The parametric models with ARX structure were considered to describe the system dynamics using transfer functions. It was hypothesized that the difference in models structure, orders, parameters, and fit can indicate different states of a driver.

Before defining a model, the data was visualized through the scatter plots to assess their quality. This assessment was based on the following criteria: (1) data points fall unreasonably far from the locations associated with the task performance, and (2) eye position data is distributed in a very unusual way. Based on this assessment, the data of four drivers was not analyzed. Thus, steering and visual behavior were compared for non-distracted and visually distracted conditions for 12 subjects through frequency histogram plots of steering angle (Figure 12) and of horizontal eye position (Figure 12b). The comparison indicated that, in general, distribution shapes for steering angle have normal tendencies with zero mean for both distraction and non-distraction conditions. However, the drivers performed differently under the two distraction conditions: when driving without distraction, the driver made some adjustments with small steering angles, but the range of the angles increased with distracted driving.

a) Steering angle (degrees)



b) Horizontal eye movement (pixel)

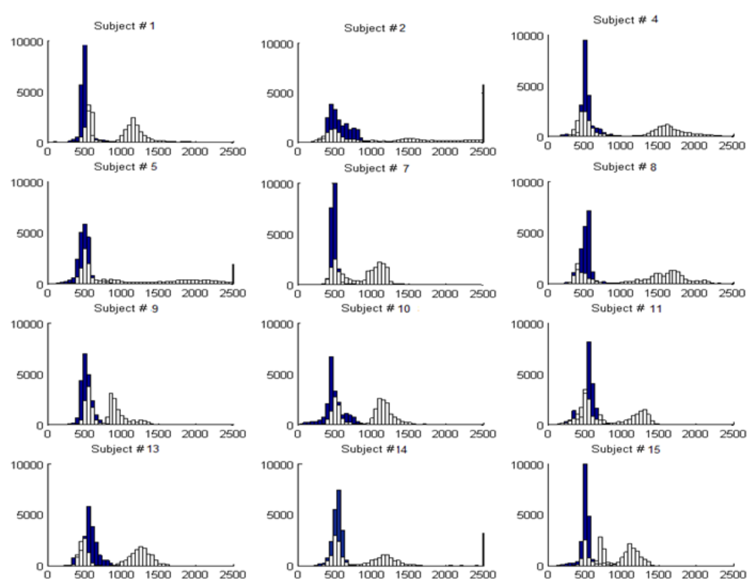


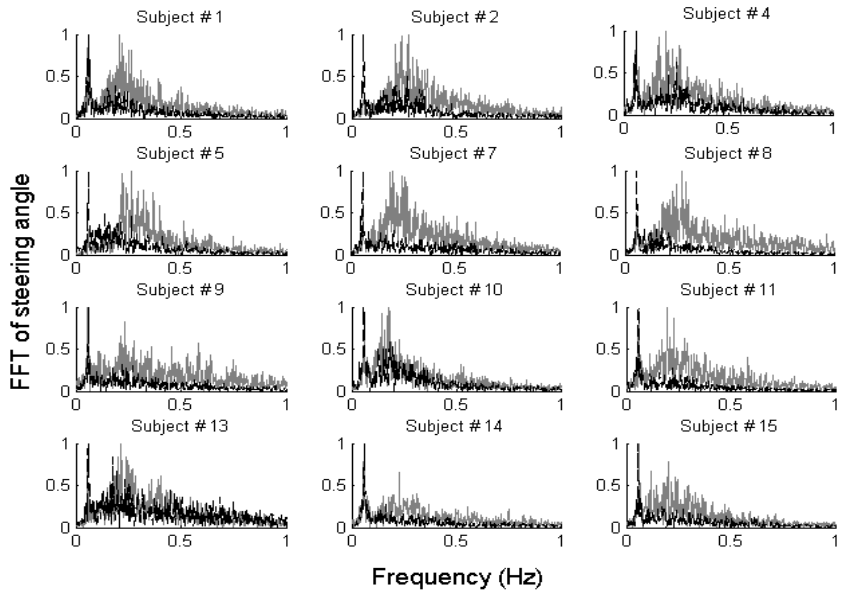
Figure 12 Distribution of (a) steering angle and (b) horizontal eye position for non-distracted (dark bars) and visually distracted (white bars) conditions

The horizontal eye position for non-distracted driving has a distribution close to normal in most cases, and it becomes bimodal (glances distributed between on-road area and off-road area) with the introduction of visual distractions, i.e., interaction with an in-vehicle display. This examination shows that driving behavior, i.e., eye and steering movements, is different across drivers. For example, subjects #2 and #5 vary from other drivers as shown by the presence of a flat distribution of horizontal eye distribution to the right of the non-distraction mode. The presence of unusual glances that could be considered as outliers (subjects 2, 5, and 14) are revealed through the visual inspection of the histograms. The presence of outliers can have a disproportionate effect on the results of correlation analysis and model definition. The outliers were defined through the rate of eye position changes: the data points are classified as outliers – sharp spikes – if the rate of eye movement exceeds the threshold value. The sets of data points classified as outliers were interpolated when the length of a segment did not exceed 400 ms (i.e., 25 data points). Since, the most common range of fixation is between 200 and 400 ms (Salvucci and Goldberg, 2000), the segments up to 400ms can be interpolated without significant distortion of eye movement information. Otherwise, the segments were deleted.

The difference in driving behavior for non-distracted and visually distracted conditions is revealed through the spectrum analysis (Figure 13): there is a shift from lower frequencies for non-distracted driving toward higher values for visually distracted driving. The average fundamental frequency in horizontal eye position signal is 0.026 Hz (cycle time of 38 seconds) and in steering angle signal is 0.069 Hz (cycle time of 14 seconds) (see also Table 8). Such a relatively low fundamental frequency (long cycle) in signals for non-distracted driving can imply that the periodic component in these signals is absent and they can be considered random (Bendat & Piersol, 1986). The signs of periodicity appear with visual distraction, when cycle lengths decrease and become 4 seconds and 6 seconds for eye and steering movements, respectively.

For eye-steering system identification, simulator driving data from Subject 2 was chosen. Here, the difference in steering performance for distracted and non-distracted driving was explicit: the distribution for distracted driving is more scattered than that for non-distracted driving (Figure 12, a). The signals were broken down into ten-second non-overlapping rectangular windows (600 samples at 60 Hz). The choice of the window size was based on the intention of determining stationary segments of data that include at least three glances and could be used without any reduction. Thus, for the model identification and validation, the segments of data that contain driving-task relevant glances were used.

a)



b)

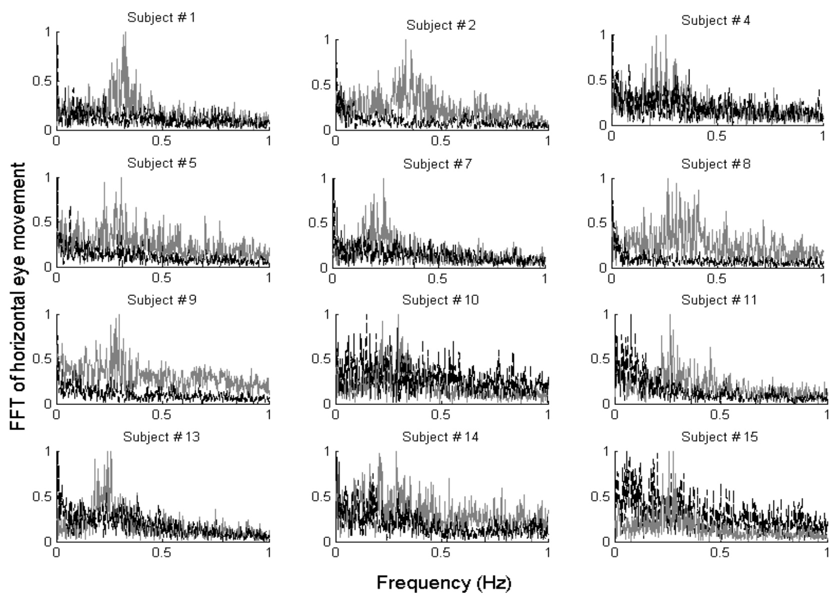


Figure 13 Detrended (a) steering angle and (b) horizontal eye position spectra for non-distracted (dashed black line) and distracted (gray solid line) conditions

The signals were detrended to remove means and any linear trend and filtered to remove high frequency components. The auto- and cross- correlation functions were calculated for both conditions. The auto-correlation functions for the non-distracted condition showed that the horizontal eye and the steering movements could be considered as random signals: the functions decrease faster than linear function (Gottman, 1981) (Figure 14).

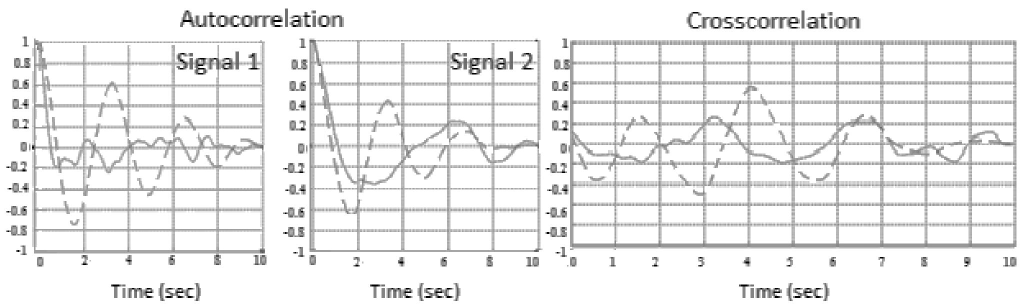


Figure 14 Auto- and cross- correlation functions calculated for eye and steering signals for 10-second segments of non-distracted (solid line) and distracted (dashed line) conditions

The correlation between signals was low. The auto-correlation functions suggest periodicity and strong coupling in the distracted condition. This periodicity might indicate glance switches between on-road and off-road areas and subsequent corrective steering movements. The cross-correlation coefficient between these signals also increased with distraction.

Eye-Steering Model Estimation

To describe the dynamics of the system by means of a transfer function and simplify the calculations, a parametric modeling approach is considered. This approach estimates the parameters or transfer functions of a specified model structure using input and output data. The advantage of parametric modeling is that the output can be easier to interpret as compared to a non-parametric approach.

Model accuracy and simplicity are two issues that should be combined in the model design: the large number of parameters can increase the precision of the model but, at the same time, can result in modeling of nonexistent dynamics and noise characteristics. The strategy used for modeling in present analysis started with the simplest design and then to increase the complexity to improve the model performance by considering noise structure, non-linearity, and an additional input (i.e., external disturbance). The non-linear structure was considered because the coherence spectrum showed that the relationship between input and output, i.e. coherence function, did not tend to one. An additional input was considered because plotting eye and steering signals with external disturbance showed that although the steering movements for some degrees are coordinated with eye glance movements, there is a probability that the external disturbance simulates some steering movements as well (Figure 15, points 3 and 4 on the graph).

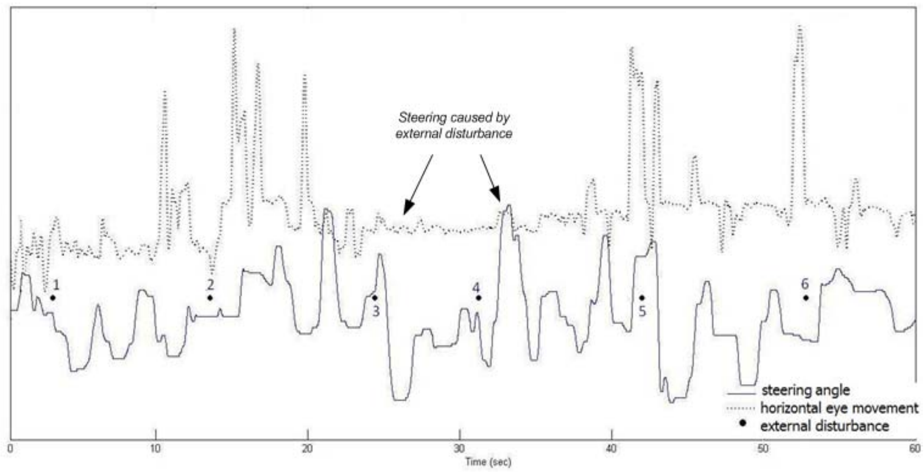


Figure 15 Steering angle and horizontal eye position (60-second sample of non-distracted driving)

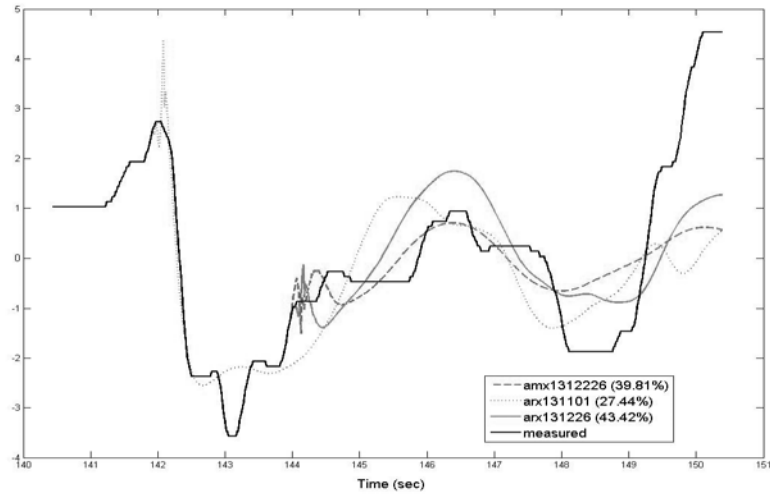
Among parametric models, the ARX model has the simplest structure defined by Equation 4. The proposed model has horizontal eye position as a single input and a single output that is a steering angle. Two different 10-second samples of simulated driving for each condition were used for model estimation and validation purposes. These two segments had similar autocorrelation function shapes. They passed the stationarity reverse arrangement test – the evaluation of statistical independence of data and underlying trends – with $\alpha = 0.05$ for steering signal and with $\alpha = 0.01$ for eye movement signal. The means were removed before starting the process of model identification.

Eye-Steering Model Validation

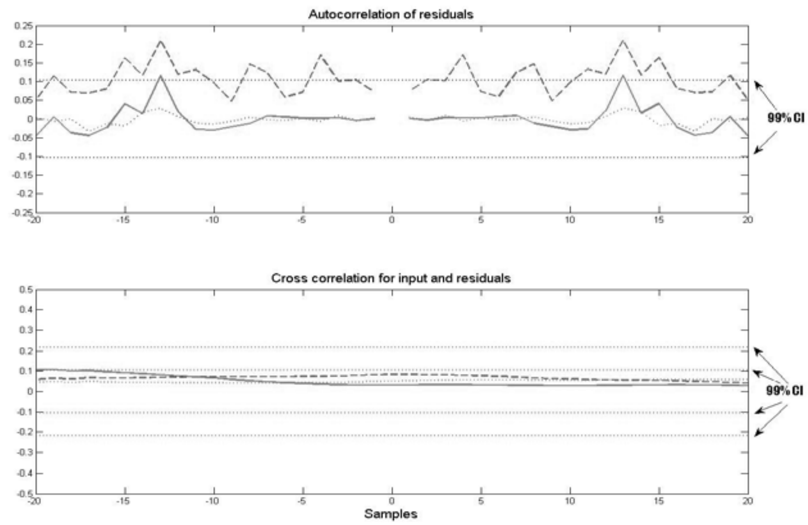
Different sets of model order ($n_a and\ n_b,$) and delay n_k were examined. The candidate models were selected based on a model accuracy measure, i.e., FPE defined by Equation 8. The best model choice was based on how well the simulated output matches the measured output (*Best Fit* value defined by Equation 9 and through the analysis of residuals. Thus, to validate the model, the models with different orders and delays that had the smallest values of FPE (similar to AIC based on Equation 8) were evaluated through the *Best Fit*. The residuals were tested on whiteness and the independence.

Different combinations of order and delay were examined to find a structure with the lowest prediction error and order. Based on this selection, three candidate models were compared for the *Best Fit* and output residuals (Figure 16). This comparison showed that the ARX model (arx131226) could be considered as the best one. In this model, the number of previous outputs on which the current output depends (n_a) is 13, and the input is delayed by 3.77 sec ($n_k = 226$). This model has the highest *Best Fit* value of 43.42 percent; and residuals passed the whiteness and independence tests with the 99 percent confidence interval (Figure 16, b).

a)



b)



c)

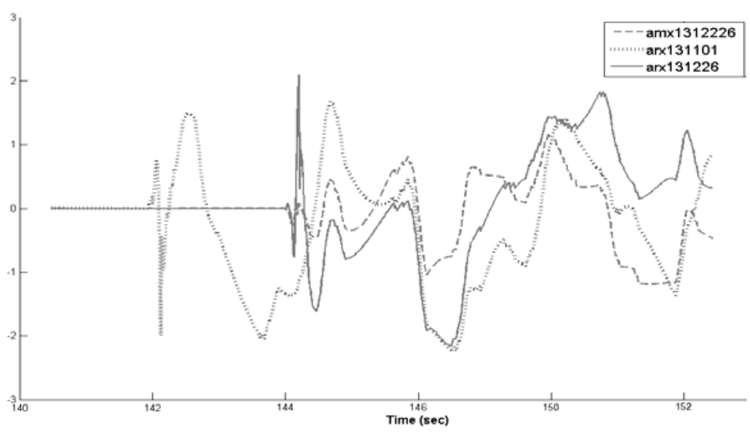


Figure 16 Comparison of candidate models for baseline driving: a) simulated and measured output comparison with Best Fit values; b) auto- and cross- correlation for residuals (the horizontal scale is the number of lags (samples) between the signals at which the correlation is estimated); and c) measured minus simulated output (error).

The consideration of the noise in the model as a separate term through the ARMAX structure (amx1312226) did not improve model performance (*Best Fit* decreased to 39.81%) (Figure 16, c). Non-linear modeling with the same structure did not improve model performance as well. Moreover, the estimation algorithm failed to converge.

Both horizontal eye position and external disturbance were used as inputs – MISO model – to define if consideration of an additional input would improve the model. The comparison of SISO and MISO models showed that the outputs for both types of models were almost the same (Figure 17).

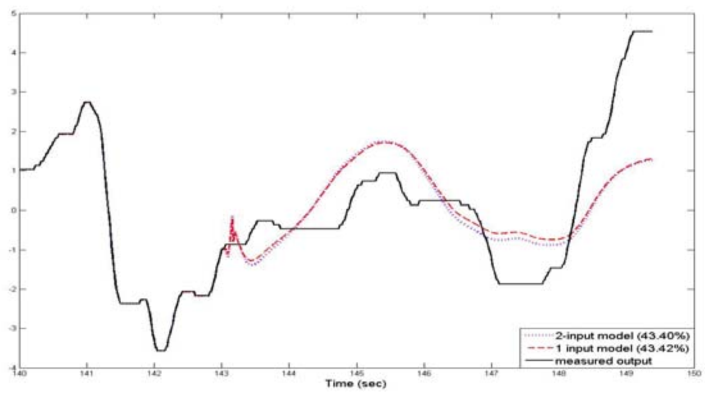
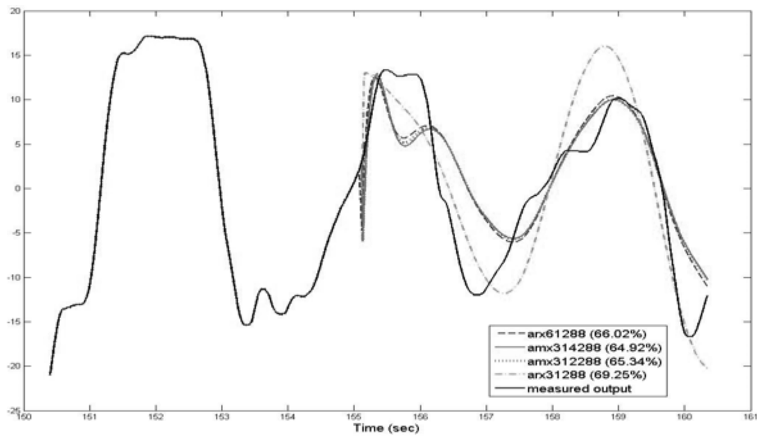


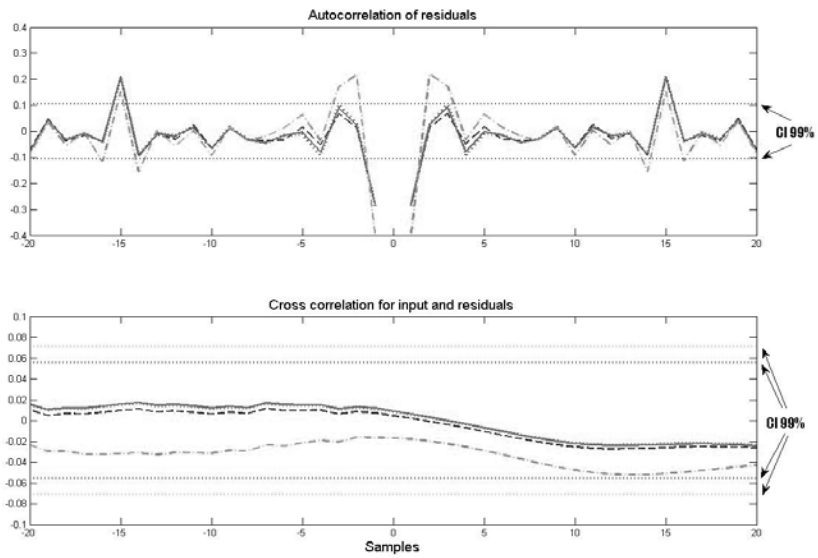
Figure 17 Comparison of SISO (one-input) and MISO (two-input) models.

For the visual task, the model selection based on FPE value showed that the influence of the input upon the output was delayed by 4.77 sec (288 samples) (Table 7). The highest *Best Fit* value had the model with the lowest order: the number of previous outputs on which the current output depends (n_a) was 3 (arx31288) (Figure 18, a). Analysis of the autocorrelation function for the residuals (whiteness test) showed that it exceeded the confidence interval of 99 percent indicating that the noise is not white (Figure 18, b). The large number of a sample size allows choosing a liberal criterion of 99 percent for the confidence interval.

a)



b)



c)

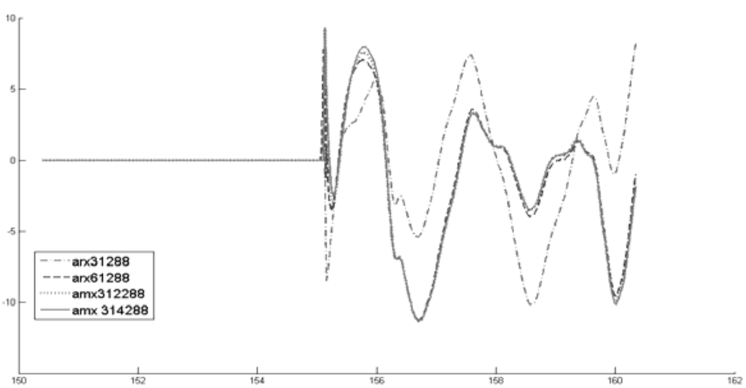


Figure 18 Comparison of candidate models for distracted driving (with visual task): a) simulated and measured output comparison with *Best Fit* values; b) auto- and cross- correlation for residuals (the horizontal scale is the number of lags (samples) between the signals at which the correlation is estimated); and c) measured minus simulated output (error).

The ARMAX model with the same structure (amx312288) improved the results of the autocorrelation function but caused *Best Fit* value decrease. The ARX model with n_a of 6 (arx61288) had similar residuals and *Best Fit* value. The error term for each structure is presented in Figure 18(c). The interesting result is that the *Best Fit* (which is similar to R^2) increases even though prediction error (FPE) increases. This result is consistent with the greater variability in steering during distraction.

Table 7 Summary of the models' estimation and validation characteristics

Models	Model order			Input delay	*Best Fit*	Prediction error
	number of previous outputs n_a	number of previous inputs n_b	number of error terms n_c	n_k (delay in seconds)	Simulated output (%)	FPE
No task						
amx1312226	13	1	2	226 (3.75)	39.81	0.002
arx131101	13	1		101 (1.68)	27.44	0.001
arx131226	13	1		226 (3.75)	43.42	0.001
arx131122677 (2 inputs)	13	1		226 (3.75)	43.20	0.001
		1		77 (1.28)		
Visual task						
arx61288	6	1		288 (4.78)	66.02	0.004
amx314288	3	1	4	288 (4.78)	64.92	0.008
amx312288	3	1	2	288 (4.78)	65.34	0.008
arx31288	3	1		288 (4.78)	69.25	0.005
nlarx31288	3	1		288 (4.78)	-10.82*	0.010

* Negative value of Best Fit indicates that estimation algorithm failed to converge

Two models with the best performance were selected to compare the transfer functions – arx131226 for non-distracted driving and amx312288 for distracted driving (Table 8). The comparison of these two models has shown that they differ by structure, parameters, time delay, and the number of the previous outputs that affected the current output. The number of the previous outputs is 13 for the non-distracted condition and 3 for the distracted one. This difference indicates that the current position of steering angle for baseline driving depends on the previous positions up to 0.22 sec (n_a=13), while this time interval for the distracted driving was very short – 0.005 sec (n_a= 3) (Table 7).

Table 8 Eye-steering system models for distracted and non-distracted driving.

Condition	Model structure	Coefficients for input, output and noise terms
Non-distracted	ARX structure: $A(q)y(t) = B(q)u(t) + e(t)$	$A(q) = 1 - 1.105\ q^{-1} - 0.2679\ q^{-2} + 0.03677\ q^{-3} + 0.1086\ q^{-4} + 0.1949\ q^{-5} + 0.1821\ q^{-6} - 0.08175\ q^{-7} - 0.05496\ q^{-8} + 0.02884\ q^{-9} - 0.02148\ q^{-10} - 0.06231\ q^{-11} + 0.05494\ q^{-12} - 0.01198\ q^{-13}$ $B(q) = -0.0001277\ q^{-226}$
Distracted (Visual task)	ARMAX structure: $A(q)y(t) = B(q)u(t) + C(q)+e(t)$	$A(q) = 1 - 2.834\ q^{-1} + 2.683\ q^{-2} - 0.8485\ q^{-3}$ $B(q) = -2.878e-006\ q^{-288}$ $C(q) = 1 - 0.9361\ q^{-1} + 0.3388\ q^{-2}$

Low correlation between input and output (Figure 14) indicates that driver steering movements do not reflect how people look at the road to guide their steering while driving on a straight road with light traffic. Non-distracted drivers mostly scan a driving environment. Driver awareness about the situation on the road led to smooth steering corrections to keep the vehicle in the lane and this could explain the greater number of the previous steering positions that influence current position. The correlation coefficient increased with distracted driving: drivers looked away from the road, then back to the road, and then made corrective steering movements. The time delay between eye and steering movements increased by 1 sec (from 3.75 for baseline driving to 4.78 for distracted driving) (Table 7). The same difference of 1 sec in time delays was observed between the peaks of the cross-correlation functions for distracted and non-distracted driving in Figure 14. This difference indicated that the visual task performance delayed the steering movement by 1 sec compared with normal driving.

Overall, the difference in transfer functions, time delays, and model structures for different distracted conditions showed that it is possible to differentiate distracted condition based on a system identification approach. The definition of a control eye–steering model could help identify impaired driving when changes in parameters or model performance are observed. However, these models defined for a single driver 10-second driving might not generalize to other drivers. Time delay as well as parameters might differ significantly for the rest of the segments of the same driver or for other drivers. The model development process presented in the next chapter is based on data from 12 drivers,

Results and Discussion

A black box modeling approach is used to construct a mathematical model of eye-steering system for all the drivers. This approach assumes that input-output data should define the parameters of the system. As it was shown in the previous section, changes in model parameters and structure might indicate changes in condition, e.g., distraction. Moreover, different types of distraction could lead to different parameters or structure (Ljung, 1987). Another approach to detect the condition changes is to develop a model for a specific condition, i.e., baseline condition, and then assess changes in model performance when data from different conditions is used as an input into the model.

This section applies the second approach and examines the hypothesis that the model defined for non-distracted driving will significantly change its performance measured through *Best Fit* (Equation 9) and residuals when data from distracted driving is used as an input into this model. The overall process of eye-steering models development and using these models for driver state identification is presented in Figure 19. The data of the same driver distracted (step1) and data of non-distracted and distracted driving from other drivers (step 2) are applied to models derived for each driver. Models performance is evaluated through *Best Fit* values. These *Best Fit* values are examined on their ability to identify presence of distraction, i.e., driver distracted condition.

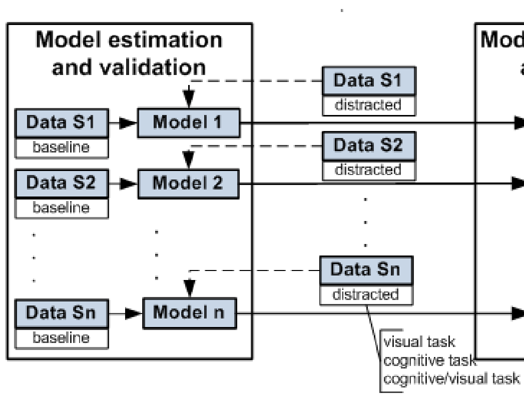


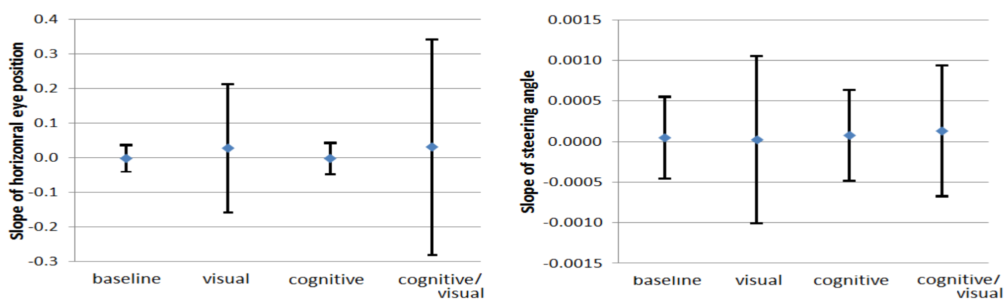
Figure 19 Schema of model development and driver state identification through model performance for a single driver (step 1). Step 2, when the data of non-distracted and distracted driving from all the drivers are applied to each model, is not shown on the schema.

For the models development, the pre-treated datasets from 12 drivers are divided on 30-second non-overlapping segments. For each driver, two different segments from baseline driving that do not contain off-road glances are used for the model estimation and validation. For this purpose, all the segments from baseline driving are examined on presence of off-road and unusual for the driving task glances. Four types of eye movement have been identified: at the road center, at driving scene, presence of glances at instrument panel, and presence of unusual driving task glances.

This classification was done to verify the hypothesis that the presence of any off-road glance, even driving related, e.g., at instrument panel, could influence model performance. The eye-steering relationship varies when a driver looks at the road from looking off the road. While looking at the road ahead, drivers get information about the driving environment and this information contributes the vehicle control, e.g., steering. This eye-steering coordination is very strong on curvy roads because eyes follow road curvature to guide steering (Land, 2006). However, while driving on a straight road, even with on-road glances, this relationship is not expected to be as strong as it was obtained on curvy roads because eye movements do not “force” steering movements. Off-road glances are also likely to change this relationship and diminish eye-steering coordination. Thus, influence of driving related (i.e., at instrument panel) and non-driving related (at in-vehicle display) off-road glances was tested.

Before models development, all the segments of data were examined for the presence of a non-zero trend, i.e., non-zero-slope straight line that best fits the data in the least squares sense. This was done to ensure that there was no need for trend modeling before system identification. Another reason for conducting the trend test is verification that the changes in model performance, when data from distracted driving is used as an input into the model, are not caused by changes in slopes.

The trend test shows that the mean slope values for steering angle and horizontal eye position were very close to zero for all the distracted conditions. The slope values deviate from zero in a wider range for visual task (M=0.028, SD=0.185) and cognitive/visual task (M=0.031, SD=0.311) compared with baseline (M=-0.002, SD=0.039) and cognitive task (M= -0.002, SD=0.045) conditions (Figure 20). These large deviations in slope values are caused by off-road glances associated with large angles.



M	-0.002	0.028	-0.002	0.031		0.000	0.000	0.000	0.000
SD	0.039	0.185	0.045	0.311		0.001	0.001	0.001	0.001

Figure 20 Slope statistics: mean values (with standard deviation bar) for non-distracted and distracted driving.

Different combinations of these off-road glances and on-road glances in 30-second segments make negative, positive, and close to zero slopes (Figure 21). The presence of the slope and its direction depends on where the off-road glances occur: the negative slope is caused by the off-road glance at the beginning of the segment; positive – at the end; and zero – in the middle or at both ends of a segment. Since, the off-road glance positioning is random, it could be concluded that slope is zero for all driving conditions. Therefore, for system identification, there is no necessity to model the trend before removing it.

Thus, before system modeling, the segments of data were detrended to remove means and any possible trend. As a part of signal preprocessing, the time series segments were filtered to remove high frequency component associated with saccades and noise (Figure 22).

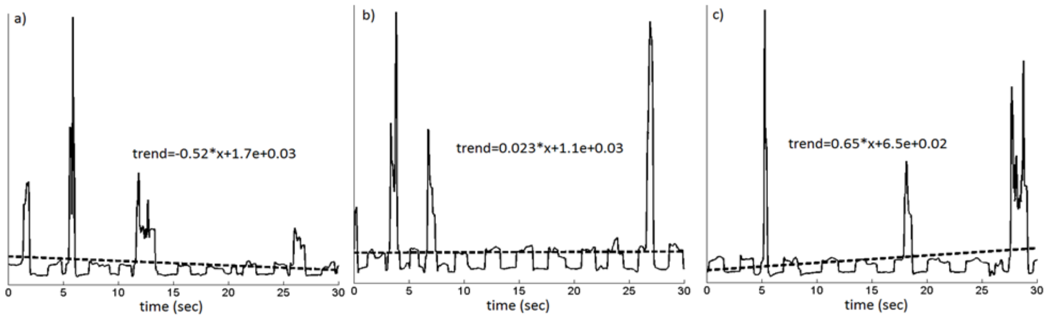


Figure 21 Trend information for 30-second segments of driving with visual task: a) negative slope; b) zero slope; c) positive slope. The conversion from pixels to angles could be done through 1:0.05 ratio.

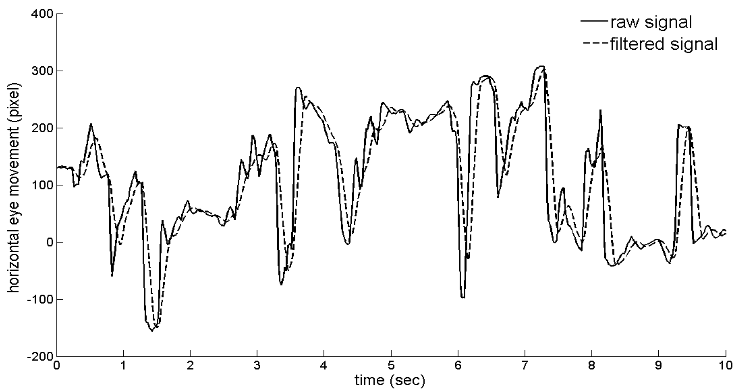
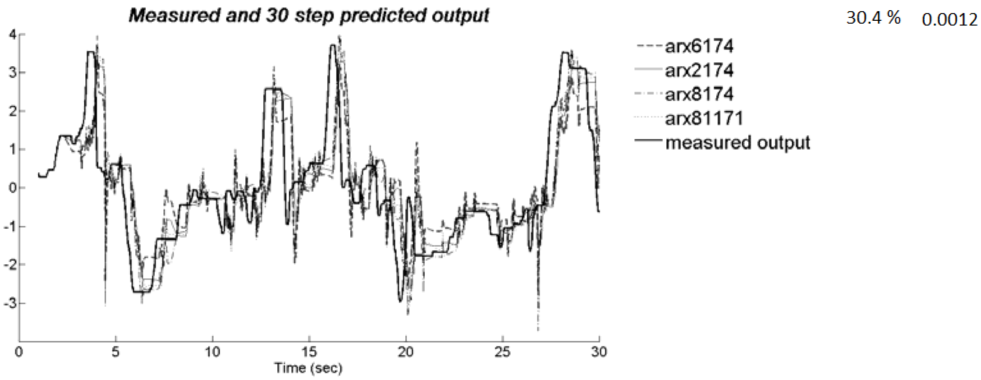


Figure 22 Comparison of a raw and filtered eye movement signal. The conversion from pixels to angles could be done through 1:0.05 ratio.

For the models development, the Matlab (R2010a) System Identification Toolbox Software (version 7.4) is used. Different sets of model structure (ARX, ARMAX, and non-linear), number of previous input and output, and time delays are examined to identify the best fitting model for each driver. The models are validated by the following criteria: (1) minimum value of FPE; (2) models should pass whiteness and the independence tests (see *Model validation* section); and (3) if more than one model passed criteria (1) and (2), the model with a minimum order is chosen.

Based on these criteria, an example of the model selection process for Subject 1 is presented on Figure 23. The models with lower order (arx2174 and arx6174) did not meet criterion (2) – they did not pass whiteness and the independence tests (Figure 23, b). For two other models (arx81171 and arx8174), the *Best Fit* and FPE values were very close; and the preference was given to the model with the smaller time delay. The consideration of the noise term (ARMAX structure) and non-linear structure did not improve model performance.

a)



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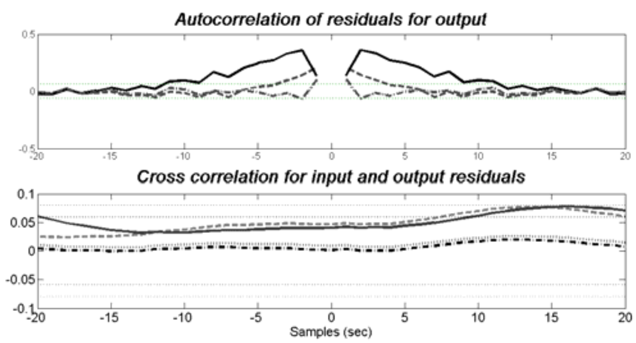
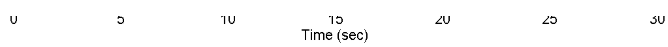




c)

Figure 23 Comparison of candidate models for non-distracted driving of Subject 1: a) 30 steps ahead predicted and measured output comparison; b) auto- and cross- correlation for residuals (the horizontal scale is the number of lags (samples) between the signals at which the correlation is estimated); and c) residuals (error).

The models are identified for all the subjects through the same procedure. The chosen models have some similarity: all the models have ARX structure, i.e. non-linearity and noise modeling (MA component) did not improve model performance; the number of previous inputs (n_b) is 1; and in most cases, the number of previous outputs (n_a) is 8 (M=8; SD=1). The number of input samples (n_k) that occur before the input that affects the output is in the range from 66 to 98 (M=78; SD=11).

The model uncertainty is evaluated through variability of estimated model parameters – means and standard deviations of coefficients generated by toolbox algorithm. These measures can be used to compare the derived models across the drivers. Assuming that the coefficients of a single model are from the normal distribution with these ARX-generated means and standard deviations (Figure 12), the coefficients are compared across the models and assessed by the degree of the confidence intervals overlap. If the coefficient confidence intervals from different models overlap, then the parameters can be considered from the same distribution (Figure 24).

This comparison is done for the first seven coefficients of the parameter A (a_1- a_7) and for a single coefficient of the parameter B (Figure 24). These graphs show that the distributions overlap for a_5, a_6, and a_7; they partially overlap for a_2,a_4, and b_{nk}; and the least overlap is for a_1 and a_3. This variability in the models' parameters is most likely due to variations in driving style among the drivers.

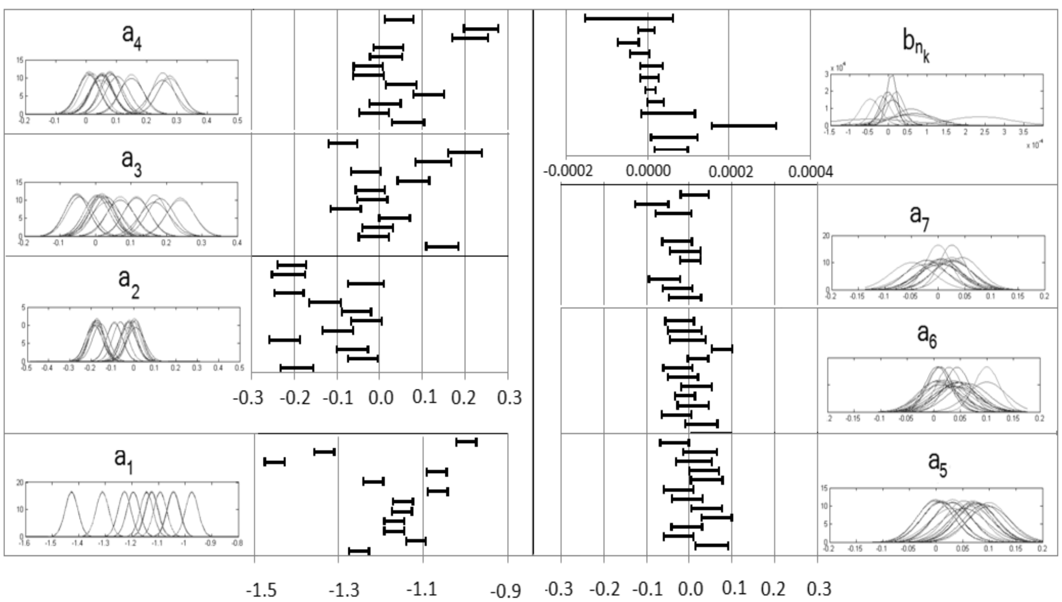


Figure 24 Model parameters variation histogram and confidence intervals across the subjects.

To assess whether model performance, measured through *Best Fit* value (9), can identify distracted driving, the models are applied to 30-second segments of data from different distracted conditions, i.e., non-distracted and three types of distracted conditions. First, data from the same driver based on which the model has been developed is used. The *Best Fit* values compared 30 steps ahead predicted by the model output with measured output for each segment of data. These values are compared through a within-subject ANOVA with repeated measures using SAS 9.2 PROC MIXED procedure.

The models performance is evaluated for different segments of baseline data classified according to the eye movement type, i.e., at the road center, at driving scene, at instrument panel, and unusual glances. The *Best Fit* values are compared for model order defined as a number of previous inputs and previous outputs, time delay between input and output (delayed input), and type of eye movement. There is no significant effect of the model order ($F(1,9)=3.19$, $p=0.41$) and number of delayed inputs ($F(1,9)=0.99$, $p=0.54$). The result that the models of different orders performed equally well indicates the difference in driving behavior: the more complex driving behavior is described by the more complex model.

Different time delay between input and output might also differentiate driver state. Since the each driving session was divided on segments, the sequence of segments was examined; and it has no effect ($F(9,64)=0.74$, $p=0.67$) on *Best Fit* values. This is an expected result because there was no obvious reason for changing driving behavior (visual or steering): driving environment has not been changed and driving sessions were too short to cause changes based, for example, on fatigue.

Another expected result is that the eye movement type, defined for baseline driving through the combination of on-road and off-road glances, influences the model performance ($F(3,18)=3.63$, $p=0.03$). Pair-wise comparisons using the Tukey test show that driving related off-road glances (at instrument panel) significantly reduce the *Best Fit* values: at road center (M=36.49, SD=8.01) versus at instrument panel glances (M=26.29, SD=6.65), $t(18)=2.44$, $p=0.02$; at driving scene (M=37.25, SD=6.77) versus at instrument panel glances (M=26.29, SD=6.65), $t(18)=3.2$, $p=0.005$) (Figure 25, a). On the other hand, the presence of the glances unusual for a driving task (M=32.14, SD=6.51) does not affect the model performance significantly (at road center versus unusual glances, $t(18)=1.11$, $p=0.28$; at driving scene versus unusual glances, $t(18)=1.69$, $p=0.11$). The difference between unusual glances and glances at the instrument panel is marginally significant ($t(18)=1.78$, $p=0.09$). Because, the focus of these glances is unknown, it is hard to explain these results. In sum, the results indicate that someoff-road glances, including those that are driving related (i.e., at instrument panel), can be identified by the models derived from the segments with on-road glances.

The analysis of models' performance is carried out for all the driving conditions. It shows that the *Best Fit* values are higher for baseline and cognitive driving conditions than for visual and cognitive/visual ones (Figure 25, b). The Levene's test for homogeneity shows that the variances differ from each other, i.e., heterogeneous ($F(3,44)=2.93$, $p=0.04$). The Welch's test that accounts the inequality of variances shows that distracted condition has a statistically significant effect on model performance ($F(3,23.6)=13.33$, $p<.0001$). Between-subject factor of gender is not statistically significant for model performance across all three conditions ($F(1,10)=0.56$, $p=0.47$).

panel

a)

b)

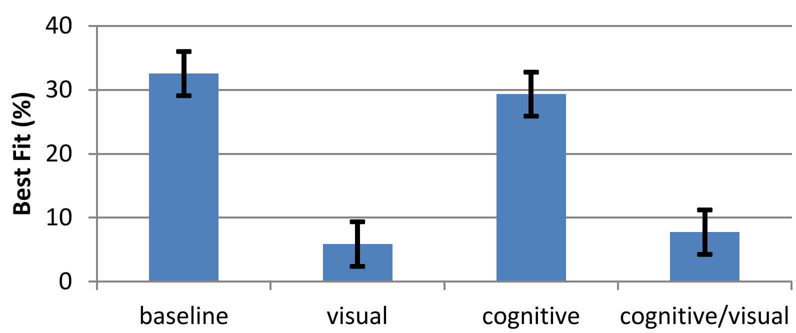


Figure 25 Model performance for (a) types of eye movement of baseline condition and (b) distracted conditions.

Post-hoc comparisons using the Tukey HSD test indicates that the *Best Fit* value for the visual condition (M=5.87; SD=20.21) is significantly different from the baseline condition (M=32.53; SD=12.32) and cognitive task condition (M = 29.33, SD = 13.64) but not for cognitive/visual, (M=7.74, SD=25.44). The *Best Fit* for cognitive condition does not significantly differ from the baseline condition. These results support the hypothesis that the model defined for baseline driving can identify distracted driving.

When the data from all the subjects is used as an input into each model from Table 9, the mean values decreased slightly across all the conditions (Figure 26). The standard deviations decreased substantially for baseline and cognitive conditions and slightly for visual and cognitive/visual conditions.

Table 9 Summary of the chosen models. The model structure is defined through number of previous inputs n_b, previous outputs n_a, and delayed inputs n_k. Standard deviations of the coefficients are in curly brackets for a_1-a_{na} and $b_{nk.}$

Model	Model structure			FPE	Parameters	
	n_a	n_b	n_k		A	B
m1	8	1	74	0.001	[-1.228;-0.155;0.183;0.104;0.090;0.065;0.027;-0.086] {0.024;0.038;0.038;0.038;0.038;0.038;0.038;0.024}	0.000058 {0.000041}
m2	9	1	67	0.019	[-1.094;-0.005;0.021;0.022;0.01;0.005;0.008;0.015;.023] {0.024;0.036;0.036;0.036;0.036;0.036;0.036;0.036;0.024}	0.000066 {0.000057}
m4	8	1	74	0.006	[-1.145;-0.027;0.031;0.049;0.030;0.045;-0.022;-0.071] {0.024;0.037;0.037;0.037;0.037;0.037;0.037;0.024}	-0.000047 {0.000079}
m5	6	1	69	0.001	[-1.145 -0.186;0.070;0.150;0.099;0.013] {0.024;0.036; 0.036; 0.036; 0.036; 0.024}	-0.000002 {0.000066}
m7	7	1	80	0.004	[-1.127;-0.062;-0.044;0.085;0.075;0.052;0.026] {0.024;0.036;0.036;0.036;0.036;0.036;0.024}	0.000237 {0.000020}
m8	8	1	66	0.007	[-1.125;0.004;0.018;0.010;0.031;0.020;0.026; 0.020] {0.024;0.036;0.036;0.036;0.036;0.036;0.036;0.024}	-0.000045 {0.000013}
m9	8	1	76	0.034	[-1.043;-0.020;0.012;0.008;0.009;0.007;0.006;0.033] {0.024;0.035;0.035;0.035;0.035;0.035;0.035;0.024}	0.000050 {0.000022}
m10	6	1	97	0.003	[-1.195;-0.090;0.116;0.052;0.077;0.044] {0.024;0.038;0.038;0.038;0.038;0.024}	0.000020 {0.000027}
m11	6	1	87	0.002	[-1.045;-0.178; 0.003;0.054;0.069;0.100] {0.024;0.035;0.035;0.035;0.035;0.024}	0.000008 {0.000023}
m13	8	1	98	0.002	[-1.427; 0.010; 0.167;0.253;0.052; 0.038;0.005;-0.096] {0.024;0.042;0.042;0.043;0.043; 0.042; 0.042;0.024}	0.000004 {0.000026}
m14	8	1	75	0.002	[-1.311;-0.173;0.239;0.276;0.065;0.029;-0.049;-0.071] {0.024;0.040; 0.040; 0.040; 0.040; 0.040;0.040;0.024}	0.000010 {0.000020}
m15	8	1	76	0.004	[-0.975;-0.172;-0.052;0.079; 0.001;0.011;0.045;0.069] {0.024;0.034;0.034; 0.034; 0.034; 0.034; 0.034; 0.024}	-0.000019 {0.000108}

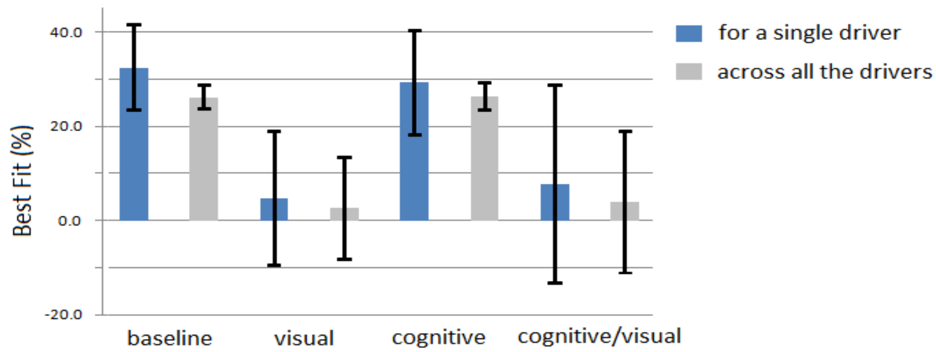


Figure 26 *Best Fit* values (with standard deviation bar) for non-distracted and distracted conditions.

An example of changes in model performance with distracted condition is in Figure 27: the model fit values decrease when the models are applied to data of visual task condition compared to baseline condition.

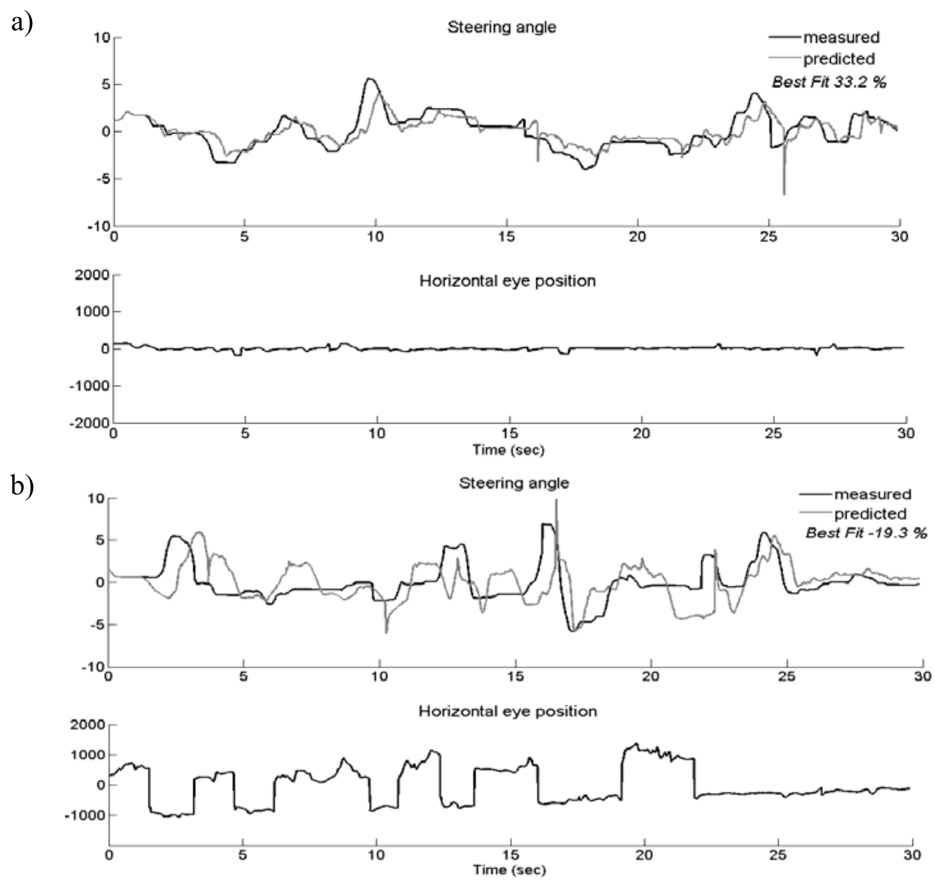


Figure 27 Measured and 30 steps ahead predicted by the model m4 output for (a) baseline condition and (b) visually distracted condition. Negative value of *Best Fit* indicates that estimation algorithm failed to converge.

To examine the models' ability to differentiate distracted driving from non-distracted driving, the classification cost/benefit analysis was performed. The receiver operating characteristic (ROC) – relationship between the hit rate and the false alarm rate – is plotted. As cut-off points, 15, 25, 50 and 75-percentiles of the *Best Fit* values of baseline driving from all the subjects are used (Figure 28). The distributions for baseline and cognitive conditions almost coincide, making classification inaccurate.

This analysis shows that all the models failed to differentiate cognitive distraction from baseline condition – the classification is no better than random guessing (Figure 29). The differentiation of visual distraction from baseline condition was the most accurate; and there was some similarity in models' performance. For cognitive/visual distraction, the models' ability to differentiate conditions varied and was less accurate than for visual distraction. Among the models, the one that most successfully differentiates visual and cognitive/visual distraction is m4 (arx8174) (Figure 30). For this comparison, the 25-percentile cut-off point is used.

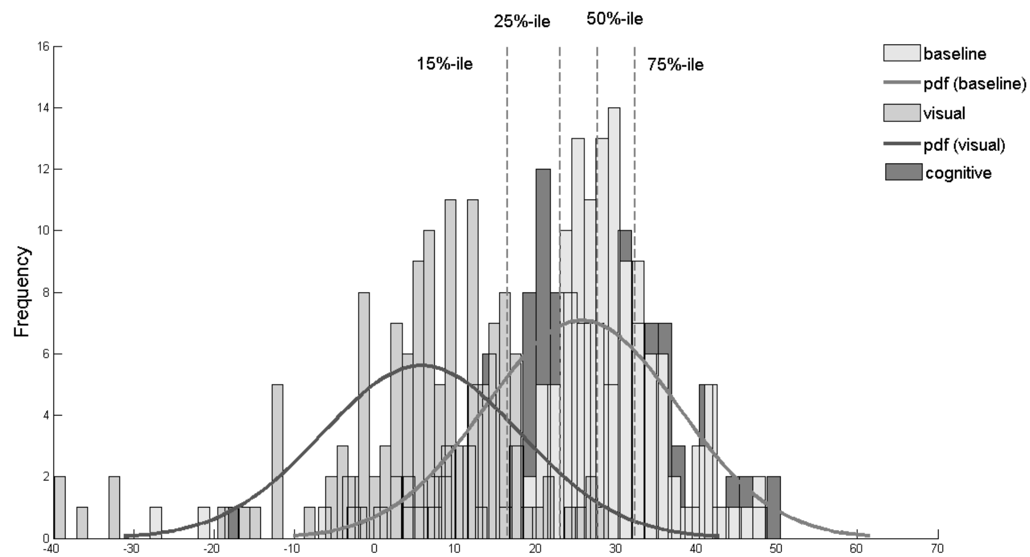


Figure 28 Distributions of the Best Fit for non-distracted, visually distracted, and cognitively distracted conditions and cut-off points. The probability density functions (pdf) for cognitive condition almost coincide with the pdf for baseline condition and is not shown on the graph.

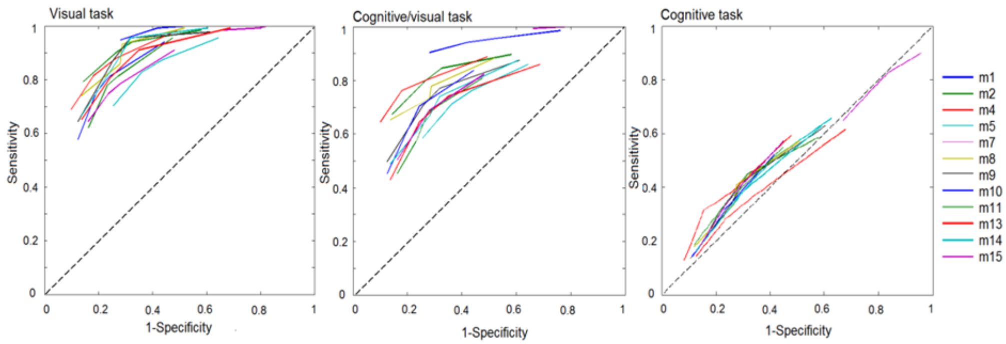


Figure 29 ROC curves. Cut-off points are defined as 15, 25, 50 and 75-percentiles of the *Best Fit* values (baseline condition).

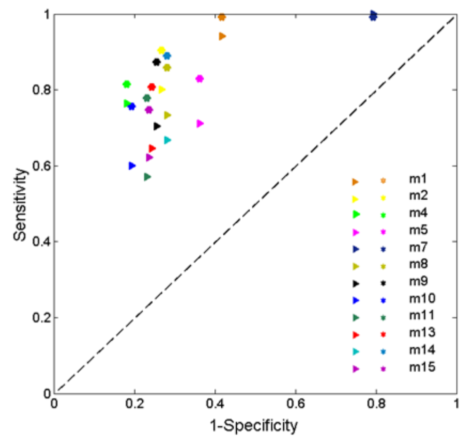


Figure 30 Models' comparison on their ability to detect distraction: triangles – for visual distraction and stars – for cognitive/visual distraction.

Conclusion

This section presents an eye-steering model for detecting distraction. This study tests the hypothesis that an eye-steering system or algorithm defined for baseline (non-distracted) condition will result in a different model fit when data from distracted conditions are used as an input to this system. According to this hypothesis, such a model can differentiate distracted driving.

The underlying theory of this hypothesis is Land's visual information and control framework. It suggests that on curvy roads gaze horizontal position is systematically coupled to roadway curvature and guides the steering movements, i.e., eye-steering coordination is strong (Land, 2006). Driver impairment might diminish this coordination. The change in coordination and associated change in model fit might accurately indicate cognitive and visual distraction.

In this assessment, it is critical to apply models derived for non-distracted driving to situations that involve glances away from the road, such as instances of visual distraction associated with off-road glances. Cognitive distraction could also diminish eye-steering coordination. These glances represent a very different type of eye movement relative to lane keeping control. When glances are directed away from the road, the relationship between eye position and steering wheel position no longer holds. The visual information input becomes zero with any off-road glance leading to reduced steering output. Returning glance back to the road provokes steering output. Thus, the system defined for non-distracted driving associated with glances at driving scene will be affected by any off-road glance.

It should be mentioned that curvy roads place a greater demand on driver eyes to guide steering and make "input" stronger than straight roads do. The eye-steering relationship on straight roads is qualitatively and quantitatively different from the one observed on curvy roads: on a straight road, drivers scan the road to be aware of the driving situation and less frequently to guide their steering. Since eye-steering correlation is weaker on a straight road, the presence of any distraction can affect this eye-steering relationship.

To confirm the hypothesis that the eye-steering system can differentiate distracted driving from non-distracted, the system identification approach is applied to define a model for each driver with horizontal eye position as an input and steering angle as an output. All the derived models have ARX model structure. The number of previous inputs (n_b) is one for all the models. In most cases, the number of previous outputs (n_a) is eight indicating that current steering wheel angle depends on previous positions up to 0.13 seconds. Based on this, the model order might decrease with re-sampling the signals to the lower rate. This reduction can be considered because both steering and eye movement signals have much lower than 60 Hz fundamental frequency – less than 1Hz (Yekhshatyan, 2010).

The number of previous outputs (n_a) and time-delay between input and output (n_k) vary across the drivers without affecting model performance. The result that the model complexity (i.e., order) does not affect model performance indicates the variability in driving behavior: the more complex model is associated with more complex driving behavior. Another support for variability in driving behavior is that some models' coefficients are similar (belong to the same distribution) but others are not.

To examine the fit of the models across drivers, the data from other drivers was used as an input into each model. Models' performance changed very little indicating that the models can perform in the same way as it was for a single driver (Figure 26). Two results that one model can fit to the data from other subjects reasonably well and that some model coefficients are from the same distribution leads to the suggestion that the model with the same structure and model order can fit to the data equally well if the particular parameters fit to individual drivers.

Attempts to select a single model that can provide a reasonable fit to the data from all the drivers led to the section of the m4 model (arx8174) shown in Equation 12:

Equation 12

$$\begin{aligned} y(t) - 1.145y(t-1) - 0.027y(t-2) + 0.031y(t-3) + 0.049y(t-4) + 0.0e30y(t-5) \\ + 0.045y(t-6) - 0.022y(t-7) - 0.071y(t-8) \\ = -0.000047u(t-74) + e(t) \end{aligned}$$

This model can differentiate visual and cognitive/visual distractions relatively successfully (Figure 30).

As was expected, off-road glances affect models' performance. The models performed worse with the presence of large-angle off-road glances (i.e., at in-vehicle display) during visual and cognitive/visual tasks. During baseline driving sessions, drivers exhibited different visual behavior: some drivers concentrated their glances at the road ahead and the driving scene; others moved eyes toward instrument panel and locations unexpected for driving task (classified as unusual glances). The presence of glances to instrument panel diminished model performance significantly. This result could mean that eye movement in vertical direction can also affect model performance.

The expectation that changes in relationship between eye and steering movements associated with cognitive distraction would affect the model performance is not confirmed. This expectation was based on sensitivity of time delay between eye and steering movement to cognitive task. Cognitive distraction did not significantly affect the model fit compared with non-distracted driving. This could be explained by two reasons. First, from the correlation analysis, the time delay between eye and steering movements was changed with cognitive distraction but the correlation coefficient was not. This causes the model to be less sensitive to changes in cognitive state of a driver than that for visual distraction when both time delay and correlation coefficient vary (Yekhshatyan, 2010). Second, as it was mentioned previously, the eye-steering relationship was not expected to be very strong on straight roads as it was for curvy roads. Thus, the possible slight changes in this relationship associated with cognitive distraction do not affect model fit. Overall, based on the model performance, it was possible to identify visual and cognitive/visual distraction associated with off-road glances.

CHAPTER 3. DISTRACTION PREDICTS BREAKDOWN OF VEHICLE CONTROL

The system identification approach to using eye-steering coordination shows that (1) the eye-steering model is sensitive to off-road glances; (2) the changes in model performance are caused by changes in correlation parameters, particularly by time delay; and (3) time delay mediates changes in lane position (Yekhshatyan, 2010). These results suggest that the eye-steering system might be sensitive to breakdowns in lane keeping as well, i.e., it can predict lane departures.

For the data considered in this analysis we assume that lane departures are the consequence of high levels of distraction. Liang (2009) indicated that visual distraction severely impairs vehicle lateral control. That study defined the lane departure event as crossing the lane boundary by any part of the vehicle. This corresponds to a deviation from the lane center of more than 1.06 meters. Based on this definition, the frequency of lane departures in the present study ranged from 89 (10 drivers out of 12) to 24 (5 drivers out of 12) during visual and cognitive/visual distractions, respectively. The frequency of lane departures across the drivers is not evenly distributed: some drivers consistently crossed the lane (up to 36 times); others had a few lane departures (from 1 to 9 times); and two drivers did not experience lane departures in any conditions. The lane departures were not observed for baseline condition and only one lane departure occurred during cognitive distraction.

Analysis Method

To assess whether the eye-steering model defined for baseline driving can differentiate the segments with lane departures from the segments without it, three groups of segments are considered. Two groups of segments with and without lane departures are from the visually distracted condition and the third group of segments represents baseline driving (Figure 31). For this comparison, the data from drivers that departed the lane several times, but not consistently, were considered. Two drivers that did not experience any lane departure are not considered either. Thus, the data from eight drivers is used for this analysis.

The length of the selected segments is 6 seconds. The segments with lane departure include five seconds before and one second after the lane departure (Klauer et al., 2006; Liang, 2009). For the visually distracted condition, the interval between the segments with lane departure and without is at least 6 seconds. For the third baseline group, the segments are randomly chosen from the same eight drivers. The number of the segments in each group is equal. Model m4 (Equation 12) is used in this analysis because its performance was considered the best among all models.

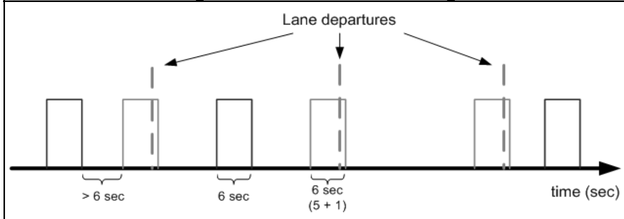
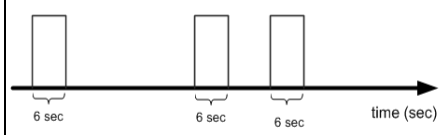
Visual distraction condition	Baseline condition
Lane departure / No lane departure	**No lane departure**
	

Figure 31 Samples of 6-second segments represent baseline and visually distracted driving with and without lane departures. Lane departures (see vertical dashed lines) are shown at the fifth second of the sample due to the method of triggering the selected sample. This allows each lane departure to have at least five seconds of history associated with it.

Results and Discussion

The sensitivity of the model to lane departures is tested through the *Best Fit* measure. The comparison of the *Best Fit* values for these three groups is done in SAS 9.2 using PROC MIXED. The results show that there is a significant difference between three groups ($F(2,14) = 8.50$, $p=0.004$): for “lane departure” group, M=13.74, SD =21.15; for visually distracted “no lane departure” group, M=8.57, SD =21.38; and for baseline condition “no lane departure” group, M= 27.77, SD=18.71. The post-hoc comparisons with Tukey HSD test indicates significant difference between baseline “no lane departure” and visual “no lane departure” groups ($t(14)=2.92$, $p=0.01$) and between baseline “no lane departure” and “lane departure” groups ($t(14)=3.99$, $p=0.001$). However, the difference between “lane departure” and visual “no lane departure” groups was not significant ($t(14)=1.09$, $p=0.30$).

Because dangerously distracted conditions that could cause lane departures are most associated with visual distraction, this result might indicate that (1) visual behavior does not differ for two groups with and without lane departures or (2) the model is not sensitive enough to off-road glances that could impact safety. To examine the former assumption, the percent of off-road glances in six-second segments (fraction of total off-road glances and segment length) was calculated. The difference in percent of off-road glances for these two visual distraction groups was not significant ($t(34)=1.63$, $p=0.11$): for “lane departure”, M= 64.58, SD = 20.74; and “no lane departure”, M=58.31, SD=23.91.

This result might indicate that driver visual behavior is not the only reason for lane-keeping performance degradation. Pohl et al. (2007) mentioned that there are many reasons for poor lane-keeping behavior, e.g., simply bad driving habits, such as task prioritization and choice of safety margins. Horrey et al. (2006) showed how task prioritizing affects visual scanning behavior and lane keeping. While performing a visual task, lane keeping was improved when drivers were concentrated on driving task and degraded with concentration only on the secondary task. Such a driving behavior associated with task prioritization might affect length and frequency of glances but not the percent of off-road glances. This might explain non-significant difference in off-road glances percent and model fit between “lane departure” and “no lane departure” groups. In addition, this driving behavior might be a primary reason of different frequencies of lane departures across the drivers.

An interesting observation that could support this assumption is made when visual behavior of two drivers who did not experience any lane departure was compared with visual behavior of two drivers that consistently crossed the lane. The percent of off-road glances was almost the same for these two driving behaviors: without lane departures, 48.78 and 57.44 and with lane departures, 48.55 and 58.30.

Another aspect to consider in the *visual behavior – lane position* relationship is the role of ambient and focal vision. The focal vision is related to eye movements and is responsible for visual search and object recognition. The ambient vision helps with spatial orientation and postural control in locomotion (Previc, 1998). Horrey et al. (2006) investigated the degree to which focal vision is responsible for visual scanning and for driving task performance. The lane-keeping task was less dependent on focal vision; it relied on ambient vision. The ambient vision can directly support vehicle control without requiring an eye movement and fixating directly on the outside world. This finding can also explain the results of this study when the eye-steering model was not sensitive to lane departures.

To assess whether the model is sensitive to off-road glances that could impact safety, the residuals were examined. Residuals represent the portion of steering angle data not explained by the model and are calculated as difference between the predicted output from the model and the measured output. The model-checking techniques suggested by Lin, Wei et al. (2002) are based on residuals comparison. This technique assumes that each observed process could be compared with another one, both graphically and numerically, through a cumulative sum of residuals. For example, trends of plotted cumulative sum of residuals could reflect differences in model fit when models with different structures are compared. The trend could change when different sets of data are used as an input into the same model. These changes could indicate different conditions such as distracted and non-distracted driving.

Thus, the residuals for the two groups of segments (with and without lane departures) for the visual distraction condition are plotted (Figure 32). To compare these two groups, sum of residuals' absolute values was calculated for each segment. This comparison shows that the group of segments with lane departure has larger sum of residuals values (M=40.4, SD=20.2) than the group of segments without lane departure does (M=26.7, SD=13.3) ($t(34)=4.41$, $p<.001$).

The cumulative sum of residuals is plotted for the segments from both groups (Figure 33, left graph). To compare these two groups, the 95 percentile values of a cumulative sum of residuals are calculated indicating the value when 95 percent of data fall below it. Each curve is fitted with a linear model. The 95 percentile values are calculated as well. This comparison of 95 percentile values shows that the group with lane departures has significantly higher 95 percentile values (M=36.0, SD = 18.2) than the group without lane departures (M=24.6, SD=12.3) ($t(34)=3.68$, $p<.001$) . The slope values of these two groups are significantly different as well ($t(34)=3.07$, $p=0.004$): for lane departure group, M=0.11, SD=0.05; and for no lane departure group, M=0.08, SD = 0.04.

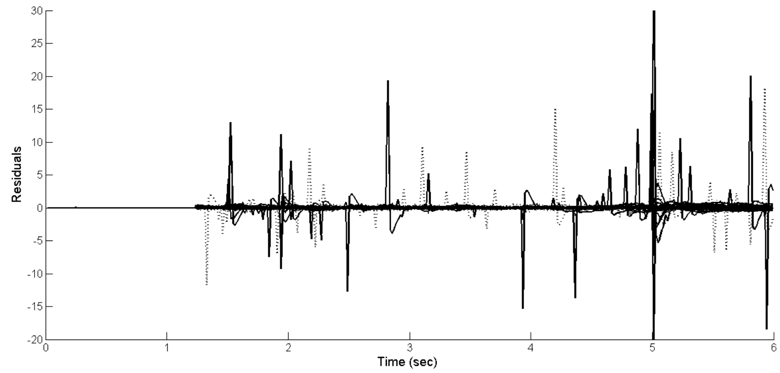


Figure 32 The residuals (predicted minus measured output) for two groups of segments with (solid line) and without (dotted line) lane departures for the visual distraction condition.

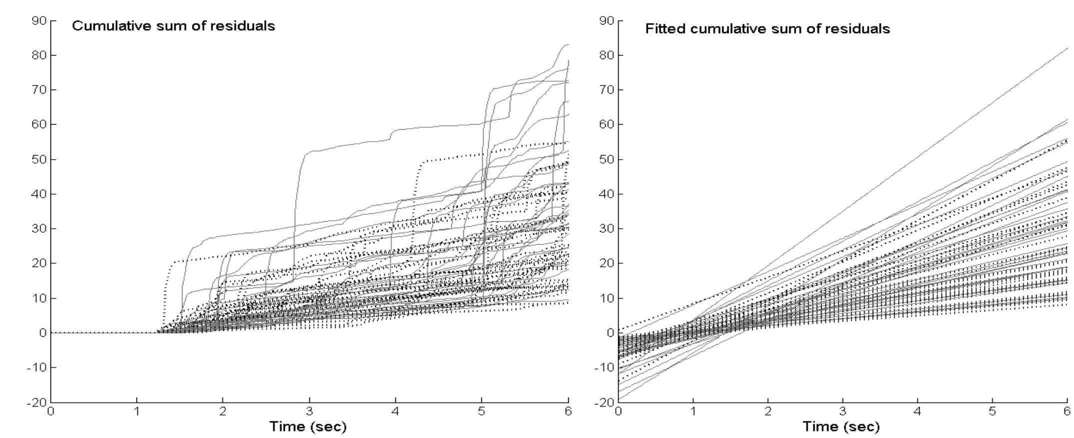


Figure 33 Cumulative sum of residuals for two groups of segments with (solid line) and without (dotted line) lane departures for the visual distraction condition (left graph) and fitted with linear regression cumulative sum of residuals (right graph). For any value x on the horizontal axis on the left graph, the corresponding value on the vertical axis is the sum of the residuals associated with the values less than or equal to x.

Thus, based only on visual behavior, e.g., percent of off-road and on-road glances, it is not possible to predict poor lane-keeping performance associated with lane departures. Other aspects of driving behavior, e.g., task prioritization, and eye movements, should be taken into account. These differences are reflected to some degree in the eye-steering model. The model is sensitive to lane departures when considering the difference in residuals for two groups of segments with and without lane departure.

Conclusion

This section examined the contribution of eye-steering correlation to *distracted condition – lane position* relationship. The correlation parameters might affect the magnitude of lane position changes associated with distraction (i.e., moderate changes) or might be considered as a mechanism that produces these changes (i.e., mediate changes). As a measure of eye-steering correlation, two parameters are considered – the correlation coefficient and time delay between eye and steering movements. This examination shows that (1) both correlation parameters do not moderate lane position changes; and (2) the correlation coefficient does not mediate the changes in lane position but time delay does.

The result that time delay, as a mediator, affects changes in lane keeping when a driver is distracted is important in terms of predicting vehicle state based on timing between visual input and steering output (Yekhshatyan, 2010). The relative timing between eye and steering movements can be used as a prospective indicator of a vehicle position in the lane. This prediction could guide distraction mitigations that might reduce crash risk caused by large deviation from centerline. Because of vehicle dynamics, a driver can be alerted before or at an early stage of these changes. This mediation is partial, i.e. time delay only partially explains changes in lane position. Thus, it is more likely that there are other mechanisms responsible for these changes; and future research should focus on examining them.

Because time delay between eye and steering movements is sensitive to distraction and affects lane-keeping performance, it was expected that an eye-steering model might be sensitive to lane departures as a result of a dangerously distracted condition. This hypothesis is tested for two groups of data from the visual distraction condition: one group of segments includes lane departures and the other does not. The selected eye-steering model performance measured through *Best Fit* did not significantly differ for these two groups. However, the analysis of residuals (predicted minus measured output) revealed differences in model performance between two groups. The total sum of residuals' absolute values and trends of cumulative sum of residuals differentiated these two groups.

An assumption that lane departures are associated with longer total off-road glances in six-second window was not confirmed: the percent of off-road glances was not significantly different for two groups(with and without lane departures) of visual task condition. Thus, although visual behavior is the indicator of poor driver performance and is associated with lane departures, it is not sufficient to predict lane departures. There are factors responsible for breakdowns in vehicle control, e.g., safety margin preferences and task prioritization. Another reason is that eye movements are associated with focal vision, but not with ambient vision that is most likely responsible for lane keeping. All these assumptions require additional examination to investigate risky driving. The interesting result is that although model performance measured through *Best Fit* was not sensitive to lane departures, the cumulative sum of residuals differs when two groups of segments with and without lane departures were compared.

Overall, an eye-steering model defined for baseline condition can distinguish not only distracted condition associated with off-road glances but can also predict breakdowns in lane keeping, i.e. lane departures. This model succeeds where simpler approaches based only on eye movement data fail.

CHAPTER 4. CONCLUSIONS

Numerous attempts have been made in the development of distraction detection algorithms. These algorithms use visual or driver performance metrics to detect visual and cognitive distractions that have the highest impact on driver performance. Several distraction detection and mitigation systems are on the market or exist as advanced prototypes; and there is a growing interest from automakers regarding the design and implementation of such distraction detection systems.

Correctly identifying driver distraction in real time is a critical challenge in distraction detection and mitigation; and this function has not been well developed. The benefit from these systems would be a prediction of risky situations associated with breakdowns in lane keeping control. This report contributes to the development of a new algorithm based on both visual behavior (eye movements) and driver performance (steering wheel movements) to detect driver distraction and predict breakdowns in lane keeping. In addition, the use of more than one source, i.e., eye and steering signals, might increase robustness and accuracy of prediction and will allow the continuous evaluation of driver distraction in case of failure of one of the input sources.

Thus the central aim of this study was to detect distraction by considering the relationship between visual and steering behavior. The underlying assumption for this rationale stems from strong eye-steering coordination observed on curvy roads where eye movements guide steering. The current study demonstrates initial attempts to evaluate eye-steering correlation on a straight road. Eye movements associated with road scanning when there is minimal need for steering leads to a low but statistically significant correlation with steering response. However, even this weak eye-steering relationship was sensitive to distraction. A model defined for a single driver successfully discriminated between distracted and non-distracted conditions for all the drivers and effectively distinguished visual and cognitive/visual distractions. Generalizing all the results, the model with the same structure and order fits to the data equally well if the particular parameters fit to individual drivers. This model can predict distraction associated with off-road glances.

Another aim of this study was to assess if the eye-steering model was sensitive to breakdowns in lane keeping. Some lane departures are a result of a dangerously distracted condition associated with off-road glances. However, the percent of off-road glances calculated for two groups of segments with and without lane departures of visual task condition was not significantly different. Thus, although visual behavior is considered as a main indicator of distraction and poor driving performance, this outcome implies that it is not a sufficient indicator of breakdowns in vehicle control. Other factors contribute to these breakdowns. Different measures of model performance were examined on their sensitivity to lane departures. The *Best Fit* values did not significantly change when the instances with lane departures were compared to the instances without lane departures from the visually distracted condition. However, the analysis of residuals revealed the differences in the total sum and cumulative sum of residuals between these two groups. This result indicates that the eye-steering system can provide a diagnostic measure of distraction in advance of mishaps.

A crucial part of this prediction is the examination of factors that can affect this correlation. Future research should focus on studying different factors (e.g., driving environment, age, and experience) that can influence the eye-steering correlation. Further, future research should examine the changes in eye-steering correlation resulting from off-road glances at different kinds of locations which vary in, for instance, road sign density, pedestrian density, road construction, and scenic roads. This examination can distinguish between different degrees of distraction indicating that some glances could be more dangerous than others. The vertical eye position could also be considered as an additional input into the model. The examination of eye-steering correlation in different driving environments provides evaluation and deeper understanding of visual-motor performance in driving.

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