Detection of Driver Distraction Using Vision-Based Algorithms

John Lee
University of Wisconsin-Madison
United States
Jane Moeckli
Department of Veterans Affairs, Iowa City VA Health Care System
United States
Timothy Brown
University of Iowa
United States
Shannon Roberts
University of Wisconsin-Madison
United States
Trent Victor
Volvo Group Trucks Technology
Sweden
Dawn Marshall
University of Iowa
United States
Chris Schwarz
University of Iowa
United States
Eric Nadler
Volpe National Transportation Systems Center
United States

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ABSTRACT

The risk of drivers engaging in distracting activies is increasing as in-vehicle technology and carried-in devices become increasingly common and complicated. Consequently, distraction and inattention contribute to crash risk and are likely to have an increasing influence on driving safety. Analysis of police-reported crash data from 2008 showed that distractions contributed to an estimated 5,870 fatalities and 515,000 injuries. This paper assesses the extent to which vision-based algorithms can detect different types of driver distraction under different driving conditions.

Data were collected on the National Advanced Driving Simulator from 32 volunteer drivers between the ages of 25 and 50. Participants drove through representative situations on three types of roadways (urban, freeway, and rural) twice: once with and once without distraction tasks. The order of the drives was counterbalanced. The three distraction tasks included a reaching task, a visual-manual task and a cognitive task which were

repeated eight times throughout the drive.

Four different vision-based algorithms were evaluated. All of them performed significantly better than chance (random) performance . There was little difference between the approaches for the visual-manual bug task which required the most eyes-off-road time. The algorithm that estimated level of distraction by combining percent of glances to the road and long glances away from the road performed best for the arrows task, and was also the only algorithm that detected cognitive impairment. Differences across road types were also observed. Trade-offs exist between ensuring distraction detection and avoiding false alarms that complicate determining the most promising algorithm for detecting distraction. The differences in the algorithms' abilities across evaluation criteria, road type, and distraction task type demonstrate critical trade-offs in capabilities that need to be considered. Depending on how feedback is presented to drivers, high false alarm rates may undermine drivers' acceptance of the system. The study shows the importance of designing and testing algorithms with a variety of challenges to assess performance across a range of representative road and task types.

INTRODUCTION

Driver distraction is occurring with greater frequency as in-vehicle technology and carried-in devices become increasingly common and complicated [1]–[3]. Consequently, distraction and inattention contribute to crash risk and are likely to have an increasing influence on driving safety. Analysis of police-reported crash data from 2008 shows that distractions account for 5,870 fatalities and an estimated 515,000 injuries [3]. It should be noted that the challenges of detecting distractions at the crash site and reluctance of drivers to admit to being distracted are a limitation for this method of estimating the linkage between distraction and injuries and fataliites. A naturalistic driving study found that distraction and inattention contribute to approximately 80% of crashes or near crashes [4]. The extent to which this generalizes from the small number of crashes that were observed in this study to the overall population of crashes remains unclear, but there is cause for concern even if the contribution is a fraction of that observed in this study.

Rapid advances in wireless, computer, and sensor technology present drivers with a range of new distractions. Not only are drivers managing their use of cell phones, CD players and navigation systems, they are increasingly engaged in long text message "conversations" and searches through MP3 music catalogs that can extend beyond 30 seconds [5] and involve more than 15 glances [6]. In the coming years, drivers will have the ability to retrieve a broad variety of information not only from the Internet via hand-held phones but also through dedicated connections in the vehicle itself. Rapid changes in vehicle design illustrate this trend: 90% of all new vehicles are compatible with MP3 players [7], all 2009 Chrysler vehicles have a wireless connection to the Internet [7], and several manufacturers introduced sophisticated Internet-enabled computers in vehicle consoles in 2010 [8]. Although these devices may have the potential to make driving more enjoyable, efficient, and potentially even mitigate drowsiness; they also have the potential to distract drivers. Helping drivers benefit from these devices and avoid distraction-affected crashes represents an important challenge.

Although efforts are afoot at state and federal levels in the US to regulate the use

of certain devices, such as hand-held cell phones, or distracting behaviors, such as the federal ban on texting by commercial truck and bus drivers [9], such regulation will likely lag behind the fast pace of technological change that is responsible for many distractions. A complementary approach that uses technology to detect and mitigate dangerous episodes of distraction, such as warnings based on long and/or frequent glances to an in-vehicle device, also has great promise in reducing the frequency and severity of distraction-affected crashes [10]. Such technological mitigations have been hampered by limitations of sensors and algorithms, but the increasing availability of improved sensor and computing technology have made more sophisticated systems possible.

The focus of this study is on the recent trend of using vehicle-based technology to combat distraction. It developed and assessed real-time distraction detection and mitigation systems to (1) guide technology development to enhance driver safety, and (2) identify potential evaluation techniques to characterize and assess this emerging technology. This paper will focus on evaluation of different algorithms for detecting driver distraction.

The overall objectives were to apply this evaluation to compare algorithm performance:

- Across road types
- Across different forms of distraction

METHOD

Participants

Data were collected on the National Advanced Driving Simulator from 32 volunteer drivers between the ages of 25 and 50. Participants drove through representative situations on three types of roadways (urban, freeway, and rural) twice: once with and once without distraction tasks. Additionally, 14 participants enrolled in the study but did not complete for various reasons.

To be eligible, participants were required to:

- Possess a valid US driver's license
- Have been licensed driver for one or more years
- Drive at least 3,000 miles per year
- Have no restrictions on driver's license except for vision
- Not have participated in simulator study in the preceding 12 months
- Have experience engaging in distracting activities while driving, such as talking on a cell phone, sending or receiving text messages, sending or receiving emails, eating, or changing compact discs

Procedure

After providing informed consent, each participant completed a demographic questionnaire that assessed their driving history, habits of interaction with distracting devices, and beliefs in their own capability as safe drivers. They then watched a presentation that described the simulator cab and the tasks they were to perform during their drives. Participants then completed three drives: an eight-minute practice drive, an experimental drive performing distracting tasks, and another experimental drive with no distractions (the latter two in a counterbalanced order) each with a duration of approximately 35-40 minutes. The practice drive acclimated the participant to the simulator and provided practice performing the distraction tasks.

After driving the urban, interstate, and rural segments, participants completed a visual-

analog scale assessing their subjective workload and performance (lateral and longitudinal control) for each distraction type. Standard simulator realism and wellness surveys were also administered after the drives, as was a post-drive survey about potential distraction mitigation strategies. A debriefing statement requesting that participants not discuss their participation with others until the end date for the data collection was provided to encourage participants to not share strategies they may have developed to perform the tasks while driving with other potential participants.

An incentive system (score) was used to encourage the participants to engage in the distracting tasks. The incentive was a function of overall task performance, including the time to initiate the distraction task, continuous attention to the task, and response accuracy. The experimenter provided scores out of 100 points to participants at the end of the three road segments in the drive with distraction tasks. Participants were told the tasks were urgent and instructed to complete as many tasks as possible while driving as they normally would.

Apparatus

The National Advanced Driving Simulator (NADS), shown in Figure 1, made it possible to collect representative driving behavior data from distracted drivers in a safe and controlled manner. The highest fidelity simulator in the United States, the NADS allowed for precise characterization of drivers' control inputs, vehicle state, driving context, and driver state during representative driving situations (see Figure 2). Eye and head tracking data is collected using a faceLAB 5™ eye tracking system.

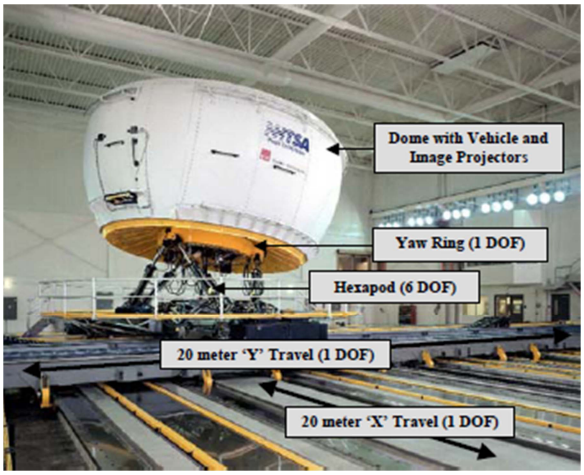

Figure 1. The NADS-1 high-fidelity driving simulator

Figure 2. An urban driving scene from the NADS-1 simulator.

Distraction Tasks

Three secondary tasks were chosen to reflect distracting activities in which drivers currently engage, like reaching toward the backseat or adjusting the radio, as well as future distractions that a distraction detection algorithm should detect. Based on the current trajectory of innovations for in-vehicle internet-based technologies and the proliferation of wireless "carried-in" devices that drivers use in vehicles, the specific activities drivers might engage in are likely to change quickly in the coming years. For this reason, generic tasks were prioritized over specific tasks that are linked to a

particular technology so that the results are more likely to accommodate the rapidly changing array of distractions that will confront drivers.

Three levels of distraction were chosen: a reaching task (bug), a visual/manual task (arrows), and a cognitive task (menu). The reaching task required drivers to reach to the back of the passenger side seat and follow a moving display with their finger similar to that used in the Crash Warning Interface Metrics program [11]. The visual/manual task was based on the arrow task used in the HASTE project [12], and presented drivers with a series of matrices of arrows on a three-inch diameter LCD touch screen located to the right of the steerig wheel. Participants had to review and discern whether or not a target arrow pointed in a particular direction was present in a field of distracter arrows. In the cognitive task, drivers traversed an interactive voice response menu that required them to respond to prompts from the system based upon information they were given concerning a fictional flight to determine if the flight was on time.

A self-paced radio task was also included but did not contribute to the protocol sensitivity analysis or algorithm evaluation except to indicate task engagement throughout the drive

Simulator Scenario

Each drive was composed of three nighttime driving segments previously used in other impairment research being conducted at NADS. The drives started with an urban segment composed of a two-lane roadway through a city with posted speed limits of 25 to 45 mph (see Figure 3 and Figure 4) with signal-controlled and uncontrolled intersections. An interstate segment followed that consisted of a four-lane divided expressway with a posted speed limit of 70 mph. After following a lead vehicle, drivers encountered several slower-moving trucks (see Figure 5) that prompted frequent lane changes. The drives concluded with a rural segment composed of a two-lane undivided road with curves (see Figure 6). A portion of the rural segment was gravel.

Distraction tasks occurred in counterbalanced blocks of three at eight points during the drive: thrice in the urban portion of the drive, twice on the interstate, and thrice in the rural portion.

Figure 3. Approach to curve in urban drive

Figure 4. Straight roadway segment in urban drive

Figure 5. Passing truck on Interstate.

Figure 6. Approach to rural curve

The Algorithms

The four algorithms evaluated in this study were chosen for their ability to distinguish between distracted and non-distracted states using eye-tracking data. The algorithms increase in complexity, and only one is designed to detect cognitive distraction.

- Eyes off forward roadway (EOFR) estimates distraction based on the cumulative glances away from the road within a 6-second window.(Dingus, Neale, Sudweeks, & Ramsey, 2006).

- Risky visual scanning patterns (RVSP) estimates distraction by combining the current glance and the cumulative glance durations [10].

- AttenD estimates distraction associated with three categories of glances (glances to the forward roadway, glances necessary for safe driving (i.e., at the speedometer or mirrors), and glances not related to driving), and uses a buffer to represent the amount of road information the driver possesses [13], [14].

- Multi distraction detection (MDD) estimates visual distraction using the percent of glances to the road center (PRC) and long glances away from the road, and estimates cognitive distraction by gaze concentration focused on the center of the road. The implemented algorithm was modified from Victor [15] to include additional sensor inputs (head and seat sensors) and adjust the thresholds for the algorithm's variables to improve robustness with potential loss of tracking.

RESULTS

Performance of the algorithms was determined using receiver operator characteristic (ROC) approach. Plots of the ROC show the true positive rate and false positive rate for algorithms across a range of detection thresholds. The best algorithms would be represented by points in the upper left and the worst by points along the diagonal. The area under the curve (AUC) measures algorithm performance and is 0.5 for the diagonal and 1.0 for a perfect algorithm.

Capabilities by Road Type

Figure 7 - Figure 9 show ROC plots comparing the performance of the algorithms across the three road types. The MDD and the EOFR algorithms performed better than the RVSP and AttenD algorithms

across all road types. The EOFR and RVSP algorithms generally performed best in the urban environment, whereas the AttenD algorithm always performed best in the rural environment. None of the algorithms performed best on all metrics in the freeway environment.

For visual distraction, the MDD algorithm showed the best performance across all evaluation metrics (accuracy, precision, AUC). Although the EOFR algorithm had promising AUC values, the AttenD algorithm often yielded better accuracy and precision. The RVSP algorithm consistently yielded the lowest values for both accuracy and precision, but yielded a slightly higher AUC value than AttenD. All of the algorithms succeeded in detecting distraction well above chance detection (AUC = 0.5).

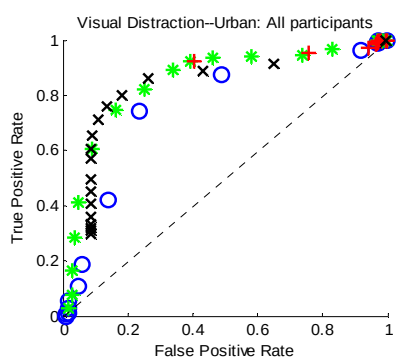

Figure 7. ROC plot in the Urban Environment for each algorithm for Visual distraction.

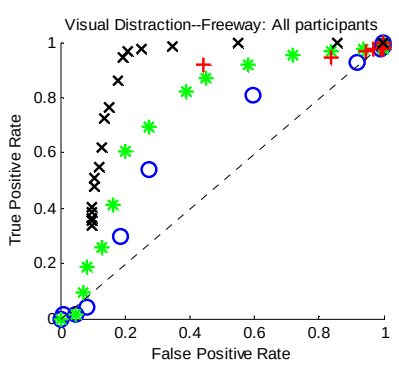

Figure 8. ROC plot in the Freeway Environment for each algorithm for Visual distraction

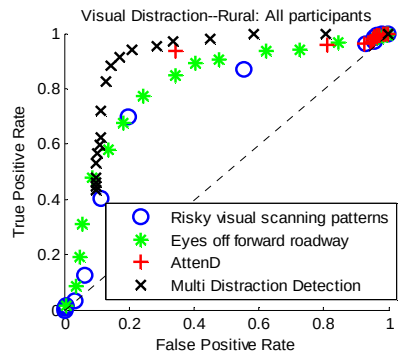

Figure 9. ROC plot in the Rural Environment for each algorithm for Visual distraction

Capabilities by Distraction Task Type

The performance of the algorithms varied by task, with little difference in performance for the looking and reaching task (bug) but more stark differences for the looking and touching (arrows) and cognitive tasks (menu). The AUC for each task for each algorithm is provided in Table 1.

Table 1. AUC comparisons by algorithm across tasks

		Algorithms			
		RVSP	EOFR	AttenD	MDD
Tasks	Arrows	0.67	0.75	0.71	0.87
	Bug	0.78	0.87	0.80	0.86
	Menu	n/a	n/a	n/a	0.68

The looking and reaching task which required the participants to turn to the backseat and follow an animated bug shown on a touch-screen display produced similar results across all four algorithms (see Figure 10). This is likely because performing the bug task sent a clear signal that the drivers' eyes were not on the road. All four algorithms performed the best during the bug task.

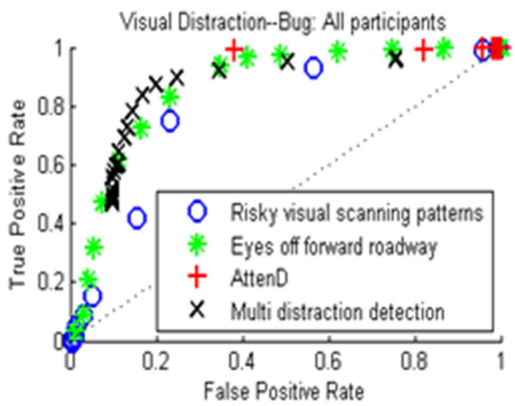

Figure 10. ROC plot for the looking and reaching task.

The looking and touching task required participants to scan a matrix of arrows located to the right of the steering wheel and identify a target. The MDD distinctly outperformed the other algorithms (see Figure 11). The AttenD algorithm yielded high true positive rates, but at the expense of high false alarm rates—the lowest false positive rate was 0.4. The two less complex algorithms (Eyes off forward roadway and Risky visual scanning patterns) performed similarly.

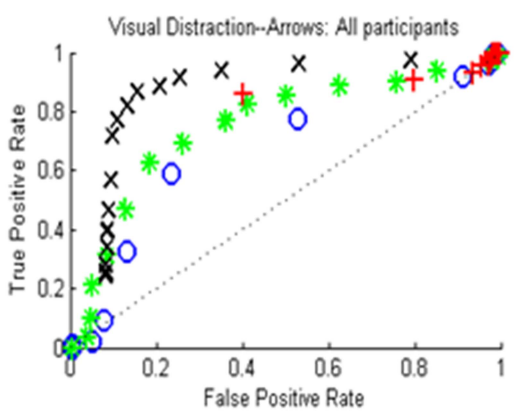

Figure 11. ROC plot for the looking and touching task.

The cognitive task required participants to access airline flight information and then to recall several pieces of flight information to determine whether a flight was on time without requiring visual attention. The MDD algorithm was the only algorithm designed to detect cognitive distraction and it did so imprecisely, but at a rate substantially greater than chance (see Figure 12).

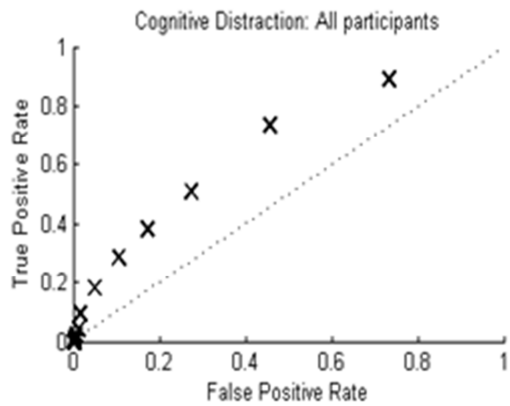

Figure 12. ROC plot for the cognitive task.

CONCLUSIONS

Considering the results of the ROC curves, AUC values, accuracy and precision, it is apparent that a trade-off exists between ensuring distraction detection and avoiding false alarms that complicates determining the most promising algorithm for detecting distraction. Depending on how feedback is presented to drivers, high false alarm rates could undermine drivers' acceptance of the system. For example, the AttenD algorithm consistently yielded high true positive rates, AUC values, accuracy, and precision, yet the lowest false positive rate exceeded 0.4. Choosing this algorithm for distraction detection would ensure detection of distraction, but it would also generate many false alarms. Depending on how this information is presented to drivers, such a high false alarm rate would likely undermine drivers' acceptance of the system.

This study demonstrates the ability for distraction detection algorithms to identify distraction with success rates much greater than chance. However, the differences in the algorithms' abilities across evaluation

criteria, road type, and distraction task type demonstrate critical trade-offs in capabilities that need to be considered. The study shows the importance of designing and testing algorithms with a variety of challenges to assess performance across a range of representative road and task types.

Further, the study shows that more complex algorithms can perform better, suggesting that additional driving metrics should be incorporated into future distraction algorithms.

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