

TRAFFIC SAFETY FACTS



Vehicle Safety Research Notes

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Distraction Detection Algorithm Evaluation

In the past 10 years, several algorithms for detecting distraction have emerged. However, there has been no uniform method for assessing and comparing these algorithms to identify which algorithms are most promising and what interventions each algorithm might support.

This study demonstrates a protocol for distraction detection algorithm assessment. The protocol consists of a data collection process that samples a selection of drivers 25 to 50 years old, driving situations (urban, rural, freeway), and representative distractions (turning, looking and reaching, looking and touching, and cognitive) designed to challenge the algorithms in a variety of ways and reveal their capabilities and vulnerabilities. The data was collected using a high-fidelity, motion-based driving simulator (NADS-1) equipped with eye- and head-tracking hardware; active feedback on steering wheel, brake pedal, and accelerator pedal; and a fully operational dashboard. Data were interpreted relative to evaluation metrics from signal detection theory.

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** (Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006): Estimates distraction based on the cumulative glances away from the road within a 6-second window.
- **Risky visual scanning patterns** (Donmez, Boyle, & Lee, 2007, 2008): Estimates distraction by combining the current glance and the cumulative glance durations.
- AttenD (Kircher, Kircher, & Ahlstrom, 2009; Kircher, Kircher, & Claezon, 2009): 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.
- Multidistraction detection (Victor, 2010): Estimates visual distraction using the percent of glances to the road center 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 by NADS to include additional sensor inputs (head and seat sensors) and adjust the thresholds for the algorithm's variables.

Figure 1.

The NADS-1 high-fidelity driving simulator.



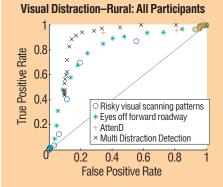
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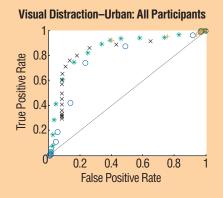
Demonstration of the reaching and looking task (bug task).

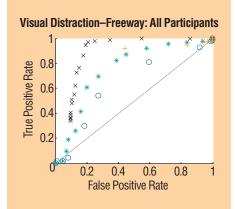


Figure 3.

ROC plots for each algorithm separated by road type







Capabilities by Road Type

Figure 3 shows receiver operator characteristic (ROC) plots comparing the performance of the algorithms across the three road types. The ROC plots 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.

The *multidistraction detection* and the *eyes-off-forward-roadway* algorithms performed better than the *risky-visual-scanning-patterns and AttenD* algorithms across all road types. The eyes-off-forward-roadway and risky-visual-scanning-patterns 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 *Multi-distraction detection* algorithm showed the best performance across all evaluation metrics (accuracy, precision, AUC). Although the *Eyes off forward roadway* algorithm had promising AUC values, the *AttenD* algorithm often yielded better accuracy and precision. The *risky-visual-scanning-patterns* 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 (AUC = 0.5).

Capabilities by Distraction Task Type

The looking-and-reaching task required the participants to turn to the backseat and follow an animated bug shown on a touch-screen display. All four algorithms performed similarly 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.

During the looking-and-touching task, the participants were required to scan a matrix of arrows located to the right of the steering wheel and identify a target. Here, the *multidistraction detection* distinctly outperformed the other algorithms. 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.

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 *multi-distraction detection* algorithm was the only algorithm designed to detect cognitive distraction and it did so imprecisely, but at a rate substantially greater than chance.

Conclusions and Implications

Considering the results of the ROC curves, AUC values, accuracy, and precision, it is apparent that a tradeoff 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.

References

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This Vehicle Safety Research Note is a summary of the technical research report: *Distraction Detection and Mitigation Through Driver Feedback* (DOT HS 811 547). This report can be downloaded free on the Vehicle Safety Research section of NHTSA's Web site (www.nhtsa.gov).

Figure 4. **ROC** plots for each algorithm separated by distraction task type Visual Distraction-Bug: All Participants 0.8 **True Positive Rate** 0.6 Risky visual scanning patterns Eves off forward roadway 0.4 0.6 0.8 False Positive Rate **Visual Distraction-Arrows: All Participants True Positive Rate** 0.4 0.6 0.8 False Positive Rate **Cognitive Distraction: All Participants** 0.8 **True Positive Rate** 0.4 0.4 0.6 0.8 False Positive Rate

