

# On Detecting Distracted Driving Using Readily-Available Vehicle Sensors: Preliminary Results

J. Dan Morrow  
 Sandia National Laboratories  
 PO Box 5800  
 Albuquerque, NM 87185  
 011-505-284-9982  
 jdmorr@sandia.gov

Kerstan Cole  
 Sandia National Laboratories  
 PO Box 5800  
 Albuquerque, NM 87185  
 011-505-284-3012  
 kscole@sandia.gov

James Davis  
 ARL Human Effectiveness Directorate  
 1st line of address  
 2nd line of address  
 Telephone number, incl. country code  
 3rd E-mail

## ABSTRACT

This paper reports on-going work in detecting distracted driving using readily-available vehicle sensors. The research executed a field study involving 67 participants driving an instrumented military vehicle (HMMWV) on dirt roads while intermittently performing a secondary, distracting task. Three different distraction tasks were employed during different runs. This poster describes the experimental protocol followed as well as early results from the analysis of the data, including the features we have generated from the raw data.

## Categories and Subject Descriptors

I. Computing Methodologies

I.5. Pattern Recognition

I.5.2 Design Methodology: Classifier design and evaluation, feature evaluation and detection, pattern analysis.

## General Terms

Algorithms, Measurement, Performance, Experimentation, Human Factors.

## Keywords

Distracted driving detection, readily-available sensors, machine learning.

## 1. INTRODUCTION

The goal of this research is to build a software-based classifier that can detect distracted driving through a stream of vehicle sensor inputs using a military vehicle on a dirt course. This work attempts to extend simulator studies that suggest that distracted driving may be captured by readily available sensors in the field. Although, this technology maybe used to develop behavioral intervention strategies in the future, the current research focuses on the detection ability of the classifier.

The sensors used to develop the classifier were restricted to those that were “readily available.” This restriction was motivated by the desire to simplify the system, to reduce expense, and to reduce dependence on exotic sensors. Further, military environments are less structured than other driving environments and may lack features that other sensors require (e.g. lane markings for lane departure sensors). In addition, military operations include a variety of weather conditions that may adversely affect more exotic sensor packages. Thus, the use of more exotic sensors may not be plausible.

## 2. EXPERIMENT

### 2.1 Experimental Method

#### 2.1.1 Participants

Sixty-seven participants, ages 22-50, drove a military HMMWV on a dirt road on Kirtland Air Force Base in Albuquerque, NM. All drivers reported possessing a current driver’s license and normal or corrected to normal vision. All participants were treated ethically and in accordance with the guidelines of APA and the HSB at Sandia National Laboratories.

### 2.2 Materials and Apparatus

#### 2.2.1 Attention light

Participants responded to an attention light, which was a cluster of LEDs was mounted in the driver’s field of view on the windshield. At random intervals, this light illuminated and participants pressed a button strapped to their thumbs in order to turn the light off as quickly as possible. This light simulated drivers’ reaction time to roadway events.

#### 2.2.2 Distraction Tasks

This set of tasks was chosen to be distracting to the driver without exposing the driver to undue risk. In particular, visuo-motor modes of interaction were specifically chosen because of their significant interference with the driving task. All of the tasks required drivers to periodically look away from the roadway and to manually interact with a touch-screen interface.

Each distraction task was randomly generated. Each distraction block was triggered by GPS location along the course. This approach ensured that each participant experienced the same distraction task presentation at the same position along the course. An auditory cue (“Begin Task”) alerts the driver to the need to perform the distraction task. A second auditory cue (“End Task”) indicates that the distraction task has completed.

#### 2.2.2.1 Short-glance task

During the short-glance task, participants monitored a series of circles on a touch screen. Participants’ task was to indicate which circle was highlighted immediately before all circles turned red. Participants accomplished this by touching the last-highlighted circle on the touch screen. This task required the driver to share visual attention between the road and the task, glancing back and forth for short periods. The overall distraction (involving approximately 10 responses) lasted approximately one minute per block. There were 13 blocks during the 30-minute experimental driving loop.

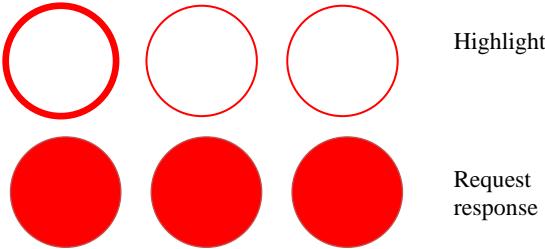


Figure 1: Dots for Short and Long Glance Tasks

#### 2.2.2.2 Long-Glance Task

The long-glance task used the same dot row previously discussed, with the exception that 4 dots were randomly presented for 500ms each followed by 100ms of OFF time. The task required participants to remember the sequence of dot presentations, and when prompted, to touch the circles in that sequence in order to score a correct answer. This task required a longer glance than the short-glance task..

#### 2.2.2.3 Table Task

Table 1 : Table Task

A	1	B	1	E	1
T	3	T	2	Z	3
C	6	Z	6	B	6
D	4	D	5	F	4
B	9	A	9	C	9
E	2	F	4	A	2
F	8	E	3	D	8
Z	5	C	7	T	5

During the table task, a six-column table was presented with alternating letter and number columns. The letters were associated with radio call signs (e.g. A=alpha, B=beta, etc.). An auditory cue was given with the call sign as the table was displayed. The task was to search each letter column for the call sign letter and to identify the digit to the right of it. Participants entered the three digit code on a touch screen keypad.. After entering the first digit, the table disappeared, requiring the driver to memorize the 3-digit sequence before entering their response. The assignment of digits to letters and the order of letter and number presentations in the table were randomly generated for each presentation.

### 2.3 Procedure

Before the experiment began, participants practiced three different distraction tasks in the stationary vehicle. Afterwards, they were instructed to maintain a 20mph speed limit and drove approximately one quarter of the course in order to gain familiarity with the vehicle. Then, they practiced each of the distraction tasks sequentially while driving.

After practice, participants executed four different driving conditions: 1) a baseline condition, in which participants drove without completing a distraction task, 2) a condition in which

participants completed the short-glance task, 3) a condition in which participants completed the long-glance task, and 4) a condition in which participants completed the table task. The order of these conditions was counterbalanced across participants. With the exception of the practice period, participants completed only one type of distraction task type within a driving loop.

The experiment took approximately 3.5 hours to complete. Afterwards, participants were debriefed and thanked for their time.

## 3. PRELIMINARY DATA ANALYSIS

### 3.1 Data Collection

The 13 vehicle data sensors used to build features included brake, throttle, steering, roll, pitch, yaw angles and rates, 3-axis accelerations, ground speed. The vehicle data was updated at 4Hz and stored in a file with timestamps along with time stamped distraction begin and end codes, response codes(correct, wrong, timeout), and abort codes. One file per participant for each of the four conditions was stored.

### 3.2 Feature Generation

The raw sensor data was processed in 5 second windows consisting of 20 samples. Features such as mean, slope, range, and standard deviation were computed. In addition, features like reversals (for steering and throttle) were computed with different gaps defining the size of a countable reversal.

### 3.3 Early Results

Using simple logistic regression, data from individual subjects was used to build a model and test its accuracy per subject. This works no better than chance on some subjects while for others (approximately 25%) we can get AUC measures between 70% and 75%. In addition, this analysis reveals that certain features, notably the reversals features, are consistently the most predictive features as indicated by their p-values across many subject models. We do not claim that this simple regression model is the best one, but rather are using it as a tool to investigate the effects of distraction on driving for different subjects. It appears that some subjects cope extremely well with the distraction task while driving as shown by a lack of predictability of distraction from driving features.

## 4. REFERENCES

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