Driver inattention detection through intelligent analysis of readily available sensors

Conference Paper · November 2004

DOI: 10.1109/ITSC.2004.1398919 · Source: IEEE Xplore

Driver Inattention Detection through Intelligent Analysis of Readily Available Sensors

Kari Torkkola, *Member, IEEE*, Noel Massey, Chip Wood, *Member, IEEE*

Abstract—**Driver inattention is estimated to be a significant factor for over 25% of all crashes. A system that could accurately detect driver inattention could aid in reducing this number. In contrast to using specialized sensors or video cameras to monitor the driver we detect driver inattention by using only readily available sensors. A classifier was trained using Collision Avoidance Systems (CAS) sensors which was able to accurately identify 80% of driver inattention and could be added to a vehicle without incurring the cost of additional sensors.**

I. INTRODUCTION

DETECTION of driver inattention could be utilized in intelligent systems to control electronic devices [1] or redirect the driver's attention to critical driving tasks [2].

Modern automobiles contain many infotainment devices designed for driver interaction. Navigation modules, entertainment devices, real-time information systems (such as stock prices or sports scores), and communication equipment are increasingly available for use by drivers. In addition to interacting with on-board systems, drivers are also choosing to carry in mobile devices such as cell phones to increase productivity while driving. Because technology is increasingly available for allowing people to stay connected, informed, and entertained while in a vehicle many drivers feel compelled to use these devices and services in order to multitask while driving.

This increased use of electronic devices along with typical personal tasks such as eating, shaving, putting on makeup, reaching for objects on the floor or in the back seat can cause the driver to become inattentive to the driving task. The resulting driver inattention can increase risk of injury to the driver, passengers, surrounding traffic and nearby objects.

The prevailing method for detecting driver inattention involves using a camera to track the driver's head or eyes [3,4]. Research has also been conducted on modeling driver behaviors through such methods as building control models [5,6] measuring behavioral entropy [7] or discovering factors affecting driver intention [8,9].

Authors are with the Intelligent Systems Lab, Center for Human Interaction, Motorola Labs, Tempe, AZ 85283 (e-mail: firstname.lastname@motorola.com).

Our approach to detecting inattention is to use only sensors currently available on modern vehicles (possibly including Collision Avoidance Systems (CAS) sensors). This avoids the additional cost and complication of video systems or dedicated driver monitoring systems. We derive several parameters from commonly available sensors and train an inattention classifier. This results in a sophisticated yet inexpensive system for detecting driver inattention.

II. DRIVER INATTENTION

A. What is Driver Inattention

Drivers' secondary activities during inattention are many, but mundane.

The 2001 NETS survey below found many activities that drivers perform in addition to driving.

NETS Survey %	Activities Drivers Engage in While Driving
96%	Talking to passengers
89%	Adjusting vehicle climate/radio controls
74%	Eating a meal/snack
51%	Using a cell phone
41%	Tending to children
34%	Reading a map/publication
19%	Grooming
11%	Prepared for work

A study, by the American Automobile Association placed miniature cameras in 70 cars for a week and evaluated three random driving hours from each.

Overall, drivers were inattentive 16.1 percent of the time they drove. About 97 percent of the drivers reached or leaned over for something and about 91 percent adjusted the radio. Thirty percent of the subjects used their cell phones while driving.

B. Causes of Driver Inattention

There are at least three factors affecting attention:

1) ***Workload.*** Balancing the optimal cognitive and physical workload between too much and boring is an everyday driving task. This dynamic varies from instant to instant

0-7803-8500-4/04/$20.00 ©2004 IEEE

and depends on many factors. If we chose the wrong fulcrum, we can be overwhelmed or unprepared.

2) ***Distraction.*** Distractions might be physical - passengers, calls, signage, etc or cognitive - worry, anxiety, aggression, etc. These can interact and create multiple levels of inattention to the main task of driving.

3) ***Perceived Experience.*** Given the overwhelming conceit that almost all drivers rate their driving ability as superior, it follows that they believe they have sufficient driving control to take part of their attention away from the driving task and give it to multi-tasking. This "skilled operator" over-confidence tends to underestimate the risk involved and reaction time required. This is especially true in the inexperienced younger driver and the physically challenged older driver.

C. *Effects of Driver Inattention*

Drivers involved in crashes often say that circumstances occurred suddenly and could not be avoided. However, due to laws of physics and visual perception, very few things occur suddenly on the road. Perhaps more realistically an inattentive driver will suddenly notice that something is going wrong. This inattention or lack of concentration can have catastrophic effects. For example, a car moving at 30 mph who has a driver that is inserting a CD for 2.0 seconds will have the same effect as an attentive driver going 52 mph. This is an equivalent increase in speed of over 20 mph. Simply obeying the speed limits may not be enough.

D. *Measuring Driver Inattention*

Many approaches to measuring driver inattention have been suggested or researched. Dingus's suggested [10] three parameters: average glance length, number of glances, and frequency of use. The glance parameters require visual monitoring of the drivers face and eyes. Another approach is using the time and/or accuracy of a surrogate secondary task such as Peripheral Detection Task (PDT) [11]. These measures are yet not practical real time measures to use during everyday driving.

Boer [12] used a driver performance measure, steering entropy, to measure workload, which unlike eye gaze and surrogate secondary-tasks, is unobtrusive, practical for everyday monitoring, and can be calculated in near real time. Our work indicates that it is able to detect driver inattention while engaged in secondary tasks. Our current study expands and extends this approach and looks at other driver performance variables, as well as steering entropy, that may indicate driver inattention during a common driving task, looking in your "blind spot".

III. Experimental Setup

A. *Driving Simulator*

Using scenario driven research, a Driver Advocate™ (DA) [2] system is being designed to advise the driver about potentially unsafe situations based on information from environmental sensors [13]. DA is an intelligent, dynamic system that monitors, senses, prioritizes, personalizes, and sends alerts to the driver appropriate to the moment. This has the potential to sharply decrease driver distraction and inattention.

To support the realization of DA, a DA Authoring Tool (DAAT) has been developed to coordinate with a DriveSafety driving simulator and allow the merging of the simulated driving performance, the environmental sensors, and the intelligent use of audio, visual, and tactile feedback to alert the driver to potential danger and unsafe driving behavior.

The simulator consists of a complete (minus drive train) 1997 Saturn automobile positioned within life-size projected 3-channel front & 1-channel rear video screens (Figure 1). It is equipped with high fidelity audio and sub-woofers, full force feedback in steering wheel and pedals, and climate controlled cab, but no hydraulic chassis motion. All driver controls such as steering wheel, brake, accelerator are monitored and affect the motion through the virtual world in real-time. Various hydraulics, air pressure, and motors provide realistic force feed back to driver controls to mimic actual driving. The simulator setup has been enhanced by adding several video cameras, microphones, and eye tracking infrared sensors to record all driver actions during the drive.

Figure 1: The driving simulator

The simulator hardware and software are combined with Motorola proprietary experimental capabilities that allow complex intelligent experimental capability through the DA Authoring Tool and complex interaction with the virtual simulation environment through Motorola DASP interface which is a Motorola designed and supported protocol.

B. Data Collection

The collection system captures data from three different applications- 1) Driver Advocate, 2) the DriveSafety simulator, and 3) the SeeingMachines eye/head tracker. These databases collect approximately 425 variables either at 60 frames/sec or as event markers. In addition, cabin audio and video of four different views of the driver and environment is digitally captured in MPEG2. All this data and audio/video is time synced, annotated, and analyzed by Motorola proprietary software. The combined databases and video produce approximately 400Mb of data for each 10 minutes of drive time.

The data collected contains almost the entire scope of the driving virtual world – the auto, the driver and his performance, the environment, and traffic. This allows a complete analysis of virtually everything that occurs during a drive. Since this complete knowledge of the world would be prohibitively expensive (if indeed, doable) in a real vehicle, we chose to focus on a very limited set of sensors that are readily available in current model cars.

C. Experiment Design

We designed the following procedure to elicit defined moments of normal driving inattention.

The simulator authoring tool, HyperDrive, was used to create the driving scenario for the experiment. The drive simulated a square with curved corners, six kilometers on a side, 3-lanes each way (separated by a grass median) beltway with on- and off-ramps, overpasses, and heavy traffic in each direction. All drives used daytime dry pavement driving conditions with good visibility.

For a realistic driving environment, high-density random "ambient" traffic was programmed. All "ambient" vehicles simulated alert, "good" driver behavior, staying at or near the posted speed limit, and reacted reasonably to any particular maneuver from the driver.

This arrangement allowed a variety of traffic conditions within a confined, but continuous driving space. Opportunities for passing and being passed, traffic congestion, and different levels of driving difficulty were thereby encountered during the drive.

After two orientation and practice drives, we collected data while drivers drove about 15 minutes in the simulated world. Drivers were instructed to follow all normal traffic laws, maintain the vehicle close to the speed limits (55 mph, 88.5 kph), and to drive in the middle lane. At 21 "trigger" locations scattered randomly along the road, the driver received a short burst from a vibrator located in the seatback on either the left or right side of their backs. This was their alert to look in their corresponding "blind spot" and observe a randomly selected image of a vehicle projected there. The image was projected for 5 sec and the driver could look for any length of time he felt comfortable. They were instructed that they would receive "bonus" points for extra money for each correctly answered question about the images. Immediately after the image disappeared, the experimenter asked the driver questions designed to elicit specific characteristics of the image- i.e. What kind of vehicle was it?, Were there humans in the image?, What color was the vehicle?, etc.

D. Selecting Data

Though the simulator has a variety of vehicle, environment, cockpit, and driver parameters available for our use, our goal was to experiment with only readily extractable parameters that are available on modern vehicles. We experimented with two subsets of these parameter streams: one which used only primitive driver controls (steering wheel position and accelerator pedal position), and a second subset which included the first subset but also added variables available from CAS systems (lane boundaries, and upcoming road curvature). A list of variables used and a brief description of each is displayed in Table I.

Variable	Description
steeringWheel	Steering wheel angle
accelerator	Position of accelerator pedal
distToLeftLaneEdge	Perpendicular distance of left front wheel from left lane edge
crossLaneVelocity	Rate of change of distToLeftLaneEdge
crossLaneAcceleration	Rate of change of crossLaneVelocity
steeringError	Difference between steering wheel position and ideal position for vehicle to travel exactly parallel to lane edges
aheadLaneBearing	Angle of road 60m in front of current vehicle position

Table I: Parameters used to detect inattention

E. Eye/Head Tracker

In order to avoid having to manually label when the driver was looking away from the simulated road, an eye/head tracker was used (Figure 2).

Figure 2: Eye/head tracking during attentive driving.

When the driver looked over their shoulder at an image in their blind spot this action caused the eye tracker to loose eye tracking ability (Figure 3). This loss sent the eye tracking confidence to a low level. These periods of low confidence were used as the periods of inattention. This method avoided the need for hand labeling.

Figure 3: Loss of eye/head tracking during inattentive driving

IV. DATA PROCESSING

Data was collected from six different drivers as described above. This data was later synchronized and re-sampled at a constant sampling rate of 10Hz. resulting in 40,700 sample vectors.

In order to provide more relevant information to the task at hand, further parameters were derived from the original sensors. These parameters are as follows

1. ra9: Running average of the signal over nine previous samples (smoothed version of the signal).
2. rd5: Running difference 5 samples apart (trend).
3. rv9: Running variance of 9 previous samples according to the standard definition of sample variance.
4. ent15: Entropy of the error that a linear predictor makes in trying to predict the signal as described in [12]. This can be thought of as a measure of randomness or unpredictability of the signal.
5. stat3: Multivariate stationarity of a number of variables simultaneously three samples apart as described in [14]. Stationarity gives an overall rate of change for a group of signals. Stationarity is one if there are no changes over the time window and approaches zero for drastic transitions in all signals of the group.

The operations can be combined. For example, "_rd5_ra9" denotes first computing a running difference five samples apart and then computing the running average over nine samples.

Two different experiments were conducted.

1. The first experiment used only two parameters: steeringWheel and accelerator, and derived seven other parameters: steeringWheel_rd5_ra9, accelerator_rd5_ra9, stat3_of_steeringWheel_accel, steeringWheel_ent15_ra9, accelerator_ent15_ra9, steeringWheel_rv9, and accelerator_rv9.
2. The second experiment used all seven parameters in Table I and derived 13 others as follows: steeringWheel_rd5_ra9, steeringError_rd5_ra9, distToLeftLaneEdge_rd5_ra9, accelerator_rd5_ra9, aheadLaneBearing_rd5_ra9, stat3_of_steeringWheel_accel, stat3_of_steeringError_crossLaneVelocity_distToLeftLaneEdge_aheadLaneBearing, steeringWheel_ent15_ra9, accelerator_ent15_ra9, steeringWheel_rv9, accelerator_rv9, distToLeftLaneEdge_rv9, and crossLaneVelocity_rv9.

A. Variable Selection

In variable selection experiments we are attempting to determine the relative importance of each variable to the task of inattention detection. Variable selection has two main approaches [15]: 1) The filter approach, whereby each variable alone is ranked by some criterion that reflects the importance of the variable. This has the downside of ignoring any interactions that two variables may have. 2) The wrapper approach considers each variable combination separately using the actual classifier for the task as the wrapper. The downside is a potentially huge number of possible variable combinations to train a classifier for, in order to find the optimal one by the accuracy of the classifier. On the positive side, variable interactions are accounted for. Since both of these approaches have considerable weaknesses, we are using an approach based on ensembles of learners, Random Forests RF [16]. RF constructs a forest of simple decision trees for the problem. The construction process provides a means of extracting the importance of each variable for the classification task. Thus the variables are not considered in isolation, and, moreover, the construction process is fairly quick.

We present results in Table II and Table III. These tables provide answers to the question "Which sensors are most important in detecting driver's inattention?" When just the two basic "driver control" sensors were used, some new derived variables may provide as much new information as the original signals, namely the running variance and entropy of steering. When CAS sensors are combined, the situation changes: lane position (distToLeftLaneEdge) becomes the most important variable together with the accelerator pedal. Steering wheel variance becomes the most important variable related to steering.

Variable	Importance
steeringWheel	100.00
accelerator	87.34
steeringWheel_rv9	68.89
steeringWheel_ent15_ra9	58.44
stat3_of_steeringWheel_accelerator	41.38
accelerator_ent15_ra9	40.43
accelerator_rv9	35.86
steeringWheel_rd5_ra9	32.59
accelerator_rd5_ra9	29.31

Table II: Important sensor signals for inattention detection derived from steering wheel and accelerator pedal.

Variable	Importance
distToLeftLaneEdge	100
accelerator	87.99
steeringWheel_rv9	73.76
distToLeftLaneEdge_rv9	65.44
distToLeftLaneEdge_rd5_ra9	65.23
steeringWheel	64.54
Stat3_of_steeringWheel_accel	60.00
steeringWheel_ent15_ra9	57.39
steeringError	57.32
aheadLaneBearing_rd5_ra9	55.33
aheadLeneBearing	51.85
crossLaneVelocity	50.55
Stat3_of_steeringError_crossLaneVelocity_distToLeftLaneEdge_aheadLaneBearing	38.07
crossLaneVelocity_rv9	36.50
steeringError_rd5_ra9	33.52
Accelerator_end15_ra9	29.83
Accelerator_rv9	28.69
steeringWheel_rd5_ra9	27.76
Accelerator_rd5_ra9	20.69
crossLaneAcceleration	20.64

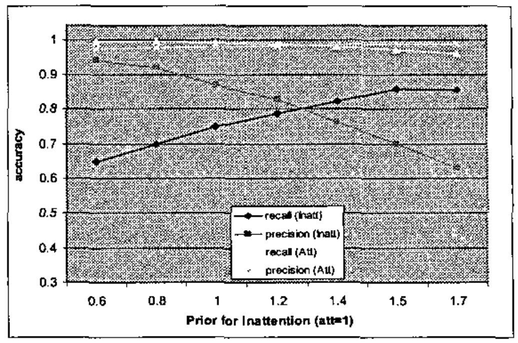
Table III: Important sensor signals for inattention detection derived from steering wheel, accelerator pedal and CAS sensors.

B. *Inattention Detectors*

Detection tasks always have a tradeoff between desired recall and precision. Recall denotes the percentage of total events of interest detected. Precision denotes the percentage of detected events that are true events of interest and not false detections. A trivial classifier that classifies every instant as a true event would have 100% recall (since none were missed), but its precision would poor. On the other hand, if the classifier is so tuned that only events having high certainty are classified as true events, the recall would be low, missing most of the events, but its precision would be high, since among those that were classified as true events, only a few would be false detections. Usually any classifier has some means of tuning the threshold of detection. Where that threshold will be set depends on the demands of the application. It is also noteworthy to mention that in tasks involving detection of rare events, overall classification accuracy is not a meaningful measure. In our case only 7.3% of the database was inattention so a trivial classifier classifying everything as attention would thus have an accuracy of 92.7%. Therefore we will report our results using the recall and precision statistics for each class.

First, we constructed a Random Forests (RF) classifier of 75 trees using either the driver controls or the driver controls combined with the CAS sensors. depicts the resulting recall/precision graphs.

One simple figure of merit that allows comparison of two detectors is equal error rate, or equal accuracy, which denotes the intersection of recall and precision curves. By that figure, basing the inattention detector only on driver control sensors results in an equal accuracy of 67% for inattention and 97% for attention, whereas adding CAS sensors raises the accuracies up to 80% and 98%, respectively. For comparison, we used the same data to train a quadratic classifier [17]. Compared to the RF classifier, the quadratic classifier performs poorly in this task. We present the results in Table IV for two different operating points of the quadratic classifier. The first one (middle rows) is tuned not to make false alarms, but its recall rate remains low. The second one is compensated for the less frequent occurrences of inattention, but it makes false alarms about 28% of the time. Random Forest clearly outperforms the quadratic classifier with almost no false alarms and good recall.



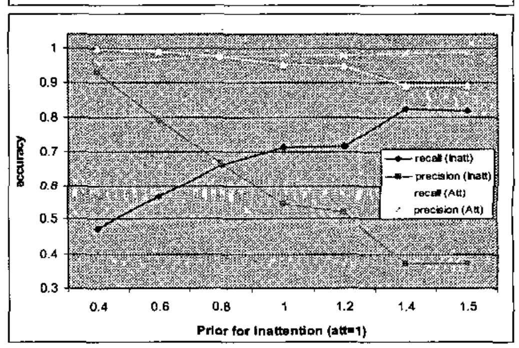


Figure 4: Precision/recall figures for detection of inattention using only driver controls (top) and driver controls combined with CAS sensors (bottom).

Detector: Sensors	Inattention	Attention
RF: Driver control sensors only	67%	97%
RF: Additional CAS sensors	80%	98%
Quadratic: Driver control sensors only	29%	91%
Quadratic: Additional CAS sensors	33%	93%
Quadratic (prior compensated): Driver control sensors only	58%	59%
Quadratic (prior compensated): Additional CAS sensors	72%	72%

Table IV: Comparison of Random Forest (RF) to Quadratic classifier using equal accuracy as the figure of merit (operating point where recall of the desired events equals the precision of the detector).

V. FUTURE WORK

The experiments described in this document are only our first steps in investigating how driver attention can be detected. We have several ideas of how to improve the accuracy of detectors based on modifications to our described approach. The first technique will be to treat inattentive periods as longer time segments that actually have a weighting mechanism that prohibits rapid toggling between states. Also, an edge detector could be trained to detect the transitions between attention/inattention states instead of states for individual time samples. Even with improvements we will end up with a less than perfect inattention detector and we will have to study user experiences in order to define levels of accuracy required before inattention detectors could be used as an acceptable driver assistant tool.

Future work should also include modeling how drivers 'recover' from inattentive periods. Even with perfect eye tracking it is unlikely that when a driver's eyes return to the road that the driver is instantly attentive and aware of his environment. This is a general attention modeling problem and is not specific to our technique.

Once driver inattention is detected there still needs to be experimentation on how to best assist the driver. Good driving habits will include periods that we have defined as inattentive, such as a 'blind spot' glance before changing lanes. The system must understand the appropriate frequency and duration of these 'blind spot' glances and not annoy the driver by offering counter-productive or unreasonable advice.

VI. CONCLUSION

Our technique explored the possibility of detecting driver inattention through use of readily available sensors. We compared both simple sensors (detecting only steering wheel angle and accelerator pedal position) and CAS sensors against the performance of a state-of-the-art eye/head tracker. As expected, the addition of CAS sensors greatly improves the ability for a system to detect inattention. Though not as accurate as eye tracking, a significant percentage of inattentive time samples could be detected by monitoring readily available sensors (including CAS sensors) and it is believed that a driver assistant system could be built to use this information to improve driver attention. The primary advantage of our system is that it requires only a small amount of additional code to be added to existing vehicles and avoids the cost and complexity of adding driver monitors such as eye/head trackers.

A driving simulator is an excellent tool to investigate driver inattention since this allows us to design experiments and collect data on driver behaviors that may impose a safety risk if these experiments were performed in a real vehicle. There is still much to be learned about the causes and effects of driver inattention, but even small steps toward detecting inattention can be helpful in increasing driver performance.

REFERENCES

[1] F. J. Pompei, T. Sharon S. J. Buckley, and J. Kemp, "An Automobile-Integrated System for Assessing and Reacting to Driver Cognitive Load", *Proceedings of Convergence 2002*, pp.411-416, IEEE SAE, 2002.

[2] D. Remboski, J. Gardner, D. Wheatley, J. Hurwitz, T. MacTavish, and R. M. Gardner, Driver performance improvement through the driver advocate: A research initiative toward automotive safety, *Proc. of the 2000 International Congress on Transportation Electronics*, SAE P-360, pp. 509–518., 2000.

[3] L. Fletcher, N. Apostoloff,, L. Petersson, A. Zelinsky, "Driver assistance systems based on vision in and out of vehicles", *Proceedings of IEEE Intelligent Vehicles Symposium*, pp. 322 – 327, June 2003.

[4] Paul Smith, Student Member, IEEE, Mubarak Shah, Fellow, IEEE, and Niels da Vitoria Lobo, Determining Driver Visual Attention With One Camera IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, VOL. 4, NO. 4, DECEMBER 2003 205

[5] R. A. Hess, A. Modjtahedzadeh, "A preview control model of driver steering behavior", *Conference Proceedings of IEEE International Conference on Systems, Man and Cybernetics.*, pp. 504 – 509, vol.2, Nov. 1989.

[6] R. A. Hess, A. Modjtahedzadeh, "A control theoretic model of driver steering behavior", *IEEE Control Systems Magazine*, vol. 10, Issue 5, pp. 3 - 8, Aug. 1990.

[7] E. R. Boer, "Behavioral entropy as a measure of driving performance", *Proc. Driver Assessment*, pp. 225–229, 2001.

[8] Oza, N. 1999. "Probabilistic models of driver behavior," presented at *Spatial Cognition Conf.* Berkeley, CA.

[9] Forbes, J., Huang, T., Kazanawa, K. and Russell, S. 1995. "The BATmobile: Towards a Bayesian Automated Taxi," *Proc. IJCAI-1995.*

[10] Hankey, J. M., Dingus, T. A., Hanowski, R. J., Wierwille, W. W.The Development of a Design Evaluation Tool and Model of Attention Demand (Virginia Tech Transportation Institute), Monk, C. A. (Science Applications Internationl Corporation), & Moyer, M. J. (Federal Highway Administration).

[11] Van Winsum, W., Martens, M. & Herland, L. (1999). The effects of speech versus tactile driver support messages on workload, driver behaviour and user acceptance. TNO-report, TM-00-C003. Soesterberg, The Netherlands.

[12] Boer, E. R. (2000) Behavioral entropy as an index of workload. Proceedings of the IEA/HFES 2000 Congress, 3, 125-128.

[13] C.Wood, B.Leivian, N.Massey, J.Bieker, and J.Summers, Driver advocate tool, *Proc. Driver Assessment*, pp. 295–299, 2001

[14] K. Torkkola. "Automatic alignment of speech with phonetic transcriptions in real time". *In Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP88)*, pages 611--614, New York City, USA, April 11-14 1988.

[15] R. Kohavi, and G. John, "Wrapper for Feature Subset Selection", Artificial Intelligence, 1997, pp. 273 – 324.

[16] L. Breiman, "Random Forests", Technical Report, University of California, Berkeley, 2001.

[17] K.Torkkola, N. Massey, B. Leivian, C. Wood, J. Summers, and S. Kundalkar. "Classification of critical driving events", *Proceedings of the International Conference on Machine Learning and Applications (ICMLA)*, pages 81–85, Los Angeles, CA, USA, June 23-24 2003.