

Autonomous Detection of Distracted Driving by Cell Phone

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Abstract— Driver distraction is a major factor in loss of life and property on our nation's highways and the broader transportation systems. The role of wireless devices as a source of distraction is well established, significant, and growing. The potential of enabling such devices with the intelligence to detect distracted cognitive states of vehicle operators is of significant interest. This paper describes a concept that enables cell phones to autonomously detect distracted driving behaviors associated with texting. Unlike conventional methods, this detection paradigm measures how texting performance is affected by driving instead of how driving performance is affected by texting, which is well documented. This new approach can be extended to other device inputs such as speech and is compatible with a spectrum of countermeasure actions to mitigate the source of distraction. A cell phone was programmed to log keystroke dynamics using a common operating system. This platform was used to characterize the texting dynamics of six subjects. Study participants were observed texting alone and, during a separate session, while texting and operating a driving simulator. This study yielded reliable distracted driving signatures that are independent of the explicit communications language and text content. This paper discusses the results in light of acknowledged distracted driving challenges, the potential of using the method for autonomous mitigation, and the speed of classification.

Index Terms— distracted driving, texting, cognitive impairment, entropy

Nomenclature—

CV	coefficient of variation
E	Shannon Entropy
NHTSA	National Highway Transportation Safety Administration
NTSB	National Transportation Safety Board
PDF	probability distribution function
ROC	receiver operational characteristic
Symbian OS	Symbian Operating System

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I. BACKGROUND

DRIVER distraction is a major factor in loss of life and suffering on our nation's highways. The role of wireless device use is well established and, unfortunately, typically discovered as a casual factor after the damage has been done. Cell phone records are routinely obtained in the aftermath of unexplained crashes all too often to find that the vehicle operator was texting or talking prior to the incident. "Driver distractions have joined alcohol and speeding as leading factors in fatal and serious injury crashes" [1]. During the First Distracted Driving Summit (September 2009) U.S. Transportation Secretary, Ray LaHood, pronounced that "Distracted driving is a deadly epidemic... On any given day in 2008, more than 812,000 vehicles were driven by someone using a hand-held cell phone... Every single time someone takes their eyes or focus off the road—even just for a few seconds—they put their lives and the lives of others in danger." The most high-profile incident involving texting while operating a motor vehicle was the September 12, 2008, crash of a commuter train in California. This tragedy resulted in the death of 25 people and the injury of more than 100. The National Transportation Safety Board (NTSB) concluded that "the probable cause of the collision was the failure of the Metrolink engineer to comply with the red signal at Control Point Topanga because he was texting on his personal wireless device, in violation of company policy. Distracted from his duties, he did not stop the train and collided head-on with the approaching freight train. He did so, despite earlier track signals and radio calls indicating he would need to stop." [2]

The National Highway Transportation Safety Administration (NHTSA) reported that 5,870 deaths and 515,000 injuries were associated with driver distraction [3]. The Harvard Center for Risk Analysis estimates that close to half of these deaths and accidents are attributable to distractions due to cell phone usage [4]. On October 1, 2009, a Presidential Executive Order, Federal Leadership on Reducing Text Messaging While Driving, was issued [5].

In April 2008, NHTSA published a report that summarized the nature of the distracted driver problem and challenges "Driver Distraction: A Review of the Current State-of-Knowledge" [6]. Several key aspects of the distracted driver problem are described. Detecting and measuring driver distraction is a major challenge "Because of the significant difficulties inherent in measuring driver attention... unlike seat belt use, the driver's attention status

cannot be categorized as “yes” or “no,” and it cannot be quantified in the same manner as blood alcohol level” (p. 3). The problem is anticipated to worsen “... the continually increasing number of cellphone users [and] the fact that phones are now being used for many more activities... specifically text messaging...” (p. 15). Common countermeasures will not be adequate to address the problem. “Standard behavioral countermeasures, including laws, enforcement, and sanctions, are considered unlikely to be effective because distraction is a broad societal problem associated with lifestyle patterns and choices” (p. 18). Most approaches to quantify driver distraction have focused on, quite reasonably, metrics associated with observations of “driving function or outcomes” to infer the level of cognitive impairment. Onboard vehicle technology solutions for detecting and measuring driver impairment will be complex. Leading research, involving the auto industry and traffic safety organizations, have consistently found that assessing the level of cognitive impairment, using behavior metrics such as eye-glance, lateral vehicle control, longitudinal vehicle control, and object-event-detection is extremely difficult. “The ultimate safety effects of new in-vehicle technologies cannot be known until the technologies are used in real-world driving, and data pertaining to drivers’ willingness to engage in the secondary tasks are obtained” (p. 4–6).

In March 2008 the NHTSA published “Driver Strategies for Engaging in Distracting Tasks Using In-Vehicle Technologies” [7]. This report analyzed driver behavior and made recommendations regarding distracted driving countermeasures. Three categories of countermeasure were described: 1) *Administrative Controls or Behavioral Countermeasures*, education and training campaigns, laws, enforcement, and sanctions; 2) *Soft Engineering Controls*, engineered solutions that aim to *reduce* the level of driver distraction from various sources. These include improvements in “device” user interface to reduce driver distraction and other driver-assist technology; and 3) *Hard Engineering Controls—Automatic Lock-out*, engineered solutions that effectively eliminate the source of distraction by disabling the device while the user is driving. An example from the automotive industry is a common lock-out feature that is incorporated into vehicle navigation systems. In this case, the navigation system is locked-out when the vehicle is in gear and/or in motion. To date, engineered controls, as applied to cell phones and other wireless digital devices pose unique challenges in determining when a countermeasure should be activated. Several currently available lock-out approaches have been proposed that are triggered by a combination of GPS signal and/or a secondary device such as pairing with the vehicle’s Bluetooth system. Other solutions rely on analyzing other elements of the device usage data via the wireless transmission. Each of these is dependent on a secondary device and/or off-board data analysis. None directly measure the level of driver

distraction nor can they reliably discriminate between a vehicle operator and a passenger. This is of particular relevance for users of mass transit and the like.

II. METHODOLOGY

The current approach is anchored in quantifying the nature of a motor vehicle operator’s interaction with a cell phone thus gaining information about the cognitive state of the user by assessing a complementary problem, “distracted texting.” Texting was chosen as it represents a high-profile cognitive workload situation. The operating hypothesis is that the texting dynamics associated with concurrent vehicle operation yields unique signatures. The experimental platform consisted of a cell phone programmed to log the duration and sequence of keystrokes. The Nokia model 6790 Surge phone was selected because it represented a common commercial device with a QWERTY keyboard. The logging application was based on the Symbian Operating System (Symbian OS). This prototype application captures key events for all letters, numbers, space, backspace, and punctuation characters such as comma, period, and question mark. Each key event is logged to a file with the following information: timestamp, event type (key up or key down), and key pressed. This data contained the standard keystroke digraph (time between keystrokes) information. All the normal data transfer functions were operable and the experimental trials involved text messaging via a commercial service.

Validation of the data logger performance was achieved by actuating keystrokes using a programmable piston as a surrogate finger. A series of evaluations were conducted with key depression frequencies of 1–10 Hz and 20 Hz. These artificial keystroke frequencies spanned the expected range for human subjects. As a point of reference, on August 23, 2010, Melissa Thompson of Manchester, England, was reported to set a world record for texting. Melissa texted a 160-character message in approximately 26 s [8]. This corresponds to a keystroke frequency of about 6 Hz. The logger demonstrated excellent performance. For example, a sampling of 100 actuations at 5.00 Hz (a period = 200 ms) yielded a mean period of 200.00 ms with a standard deviation of 3.16 ms and a coefficient of variation (CV) of 1.58%. This represents a resolution that is over 50 times greater than the interval between keystrokes of an extremely fast texter [9].

Six subjects were selected from a volunteer pool. The screening criteria were that subjects could read and text English messages from a cell phone, and the study was normalized by selecting subjects who were experienced at texting with both hands and had the use of five fingers on each hand. Each subject completed four activities in the following order: 1) a 20-minute acclimation period of texting on the study phone, 2) a 20-minute acclimation period for driving the simulator, 3) a 20-minute texting session while not driving the simulator where non-driving

texting data were collected, and 4) a 20-minute session of simultaneous texting and driving the simulator where texting and driving data were collected. While driving, participants were asked to operate the simulator safely, negotiating common traffic situations, and avoiding common traffic hazards, obstacles, etc. The simulator included a steering wheel, brake pedal, and accelerator pedal. The driving scene was displayed on a large desktop monitor. Although the simulation was not a high-fidelity replication of an actual driving experience, the challenge level was the same for all participants and was selected to approximate the frequency of traffic challenges presented by normal traffic conditions; that is, the driving task did not constitute a hyper-real, highly-stimulating gaming situation.

Texting “conversations” were simulated by asking participants to echo (return the same text message as the one received) a series of incoming text message. The library of “incoming messages” averaged 48 characters (including spaces) in length, an average of 10 words. The incoming message was randomly selected from the library without replacement. Although subjects were not quantitatively evaluated on the quality of their texting or driving, they were observed while texting alone and texting while driving.

III. RESULTS

All subjects were observed to use a two-handed texting technique when texting only. Drivers employed a variety of adaptation strategies for texting while driving. Examples were a two-handed technique for texting, with the palms placed on the top of the steering wheel; single-handed texting; and two-handed texting with hands off the steering wheel other than for intermittent steering corrections. Preliminary statistical analysis of both key hold times and digraph (time between keystrokes) data were conducted, and it was determined that the digraph data warranted priority for further analysis. Subject 245 is representative of the key findings. Fig. 1 is a histogram approximating probability density functions of the digraphs for texting only (solid line) and texting while driving (dashed line) for this subject. The dominant feature, the difference in area under the curve, reflects the difference in the volume of the text that was processed. As expected, the volume of texting while driving was less than that for texting alone. Because there are many potential contributors to variations in gross texting rate, a more mechanistically based analysis was warranted.

IV. DEVELOPMENT OF A CLASSIFICATION MODEL

It was anticipated that the text messages of subjects engaged in texting while driving would exhibit a higher level of entropy as compared to the texting data for the same subject texting alone. Entropy reflects the complexity of an activity and the information content of the associated data. Prior work involving driver steering input supports this idea

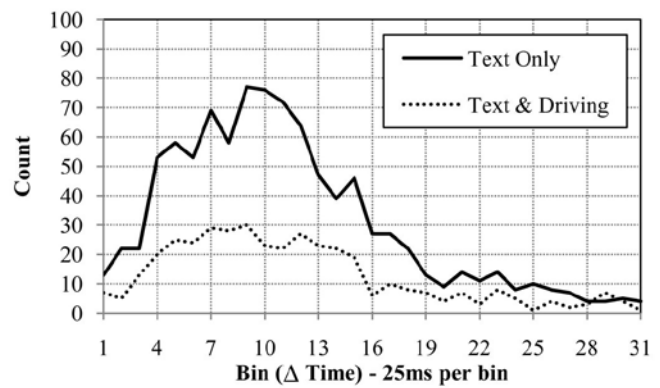


Fig. 1. Histogram approximating probability density functions of the digraphs for text only (solid line) and text while driving (dashed line) for subject 245.

and provides a mechanistic cognitive framework for developing a classification model to detect and quantify operator distraction. The action of executing a steering correction is a useful analog to depressing cell phone keys in that they both have quantifiable temporal dimensions. Specifically, it has been demonstrated that introducing a distracting task altered the frequency and amplitude distribution function of corrections in such a way as to increase the measured entropy. Boer and Nakayama concluded that increases in steering entropy are indicative of the level of driver distraction. “...*Delayed event detection and degraded vehicle control are observed when drivers fuel their need to perform extra-driving activities. Vehicle control and event detection are shown to degrade most if the in-vehicle task requires spatial cognitive resources and/or if the activity requires visual perception and/or manual control manipulation... The signature of a lack of understanding and a lack of control is an erratic, unpredictable, and inefficient behavior that we quantify with an entropy measure... These signatures are also observed in eye movements, in interaction with interfaces, and in control of dynamical systems...*” [10-12]. Steering entropy has been studied for both driving simulators and on-road driving with cell phone use as a secondary task. Other research established that an increase in steering entropy resulted from having subjects operate a driving simulator after consuming alcohol [13]. As will be discussed below, the current findings are consistent with those cited above.

Shannon Entropy (E) was investigated as a texting performance measure since, while texting and driving, the two tasks compete for some of the same cognitive resources. For discrete problems, such as this, a discrete estimate of entropy is used and is defined by (1), where the probability density function is estimated by a histogram of the data so that $p(t_i)$ is the estimated probability of an event occurring at delta time, t_i , and N is the number of bins used to form the histogram.

$$E = \sum_{i=1}^N p(t_i) \ln(p(t_i)) \quad (1)$$

The metric of merit investigated was the change in entropy ($\Delta E = E_{\text{txt w/drving}} - E_{\text{txt}}$), where $E_{\text{txt w/drving}}$ is the entropy for texting while driving and E_{txt} is the entropy while texting alone. ΔE was positive for all subjects and reflected a fundamental increase in the complexity of the driver's activity and the information content of the texting data. The entropy data were used to investigate a very practical question: What is the sensitivity of entropy to the number (n) of sampled keystrokes? This was investigated using a Monte Carlo technique. It should be noted that this preliminary analysis assumes a worst-case sampling scenario, equal sample sizes for non-driving and driving keystrokes. A more realistic and favorable scenario is that the non-driving baseline sample size will be much larger than the sample size for evaluation, allowing for more rapid detection of driver inattention. Thus the assessment of the method reliability presented below represents a conservative evaluation. The Monte Carlo method yielded an estimate of the entropy probability distribution functions (PDF) for each subject under both texting conditions. The result was an estimate of the PDF that was then used to calculate $E(n)$. Fig. 2 is an example of the observed increase in separation of the entropy distributions as the number of keystrokes was increased from 100 to 500. Distinct and significant distribution shifts were observed for each participant.

The feasibility of using an entropy-based discriminator for texting while driving was further evaluated by generating Receiver Operational Characteristic (ROC) curves. These revealed that, for all except one behavioral outlier (discussed below), it is possible to make a highly reliable (true positive rates $> 99.0\%$ with false positive rates $< 1.0\%$) classification. The ROC curves for subjects #369 and #281 are indicative of a nearly ideal response for $n \geq 100$. Subjects #245, #473, and #750 required a higher sample ($n \geq 500$) to achieve these rates. Although the qualitative change in entropy distribution was the same for subject #592 as for the other participants, the quantitative difference was strikingly smaller. This can be explained by considering the observed driving behavior of this participant. During the simulated driving while texting phase, subject #592 was observed to engage in more off-road and in what can be described as high-risk driving behavior. This was accompanied by a higher number of traffic incidents than any of the other participants. It is very unrealistic to expect that this level of bias toward attention to the cell phone task would be observed for on-road driving since the increased real and perceived risk would result in redirecting attention away from texting and toward driving. It is anticipated that, for on-road driving, subject #592 would exhibit quantitative differences in entropy distribution and

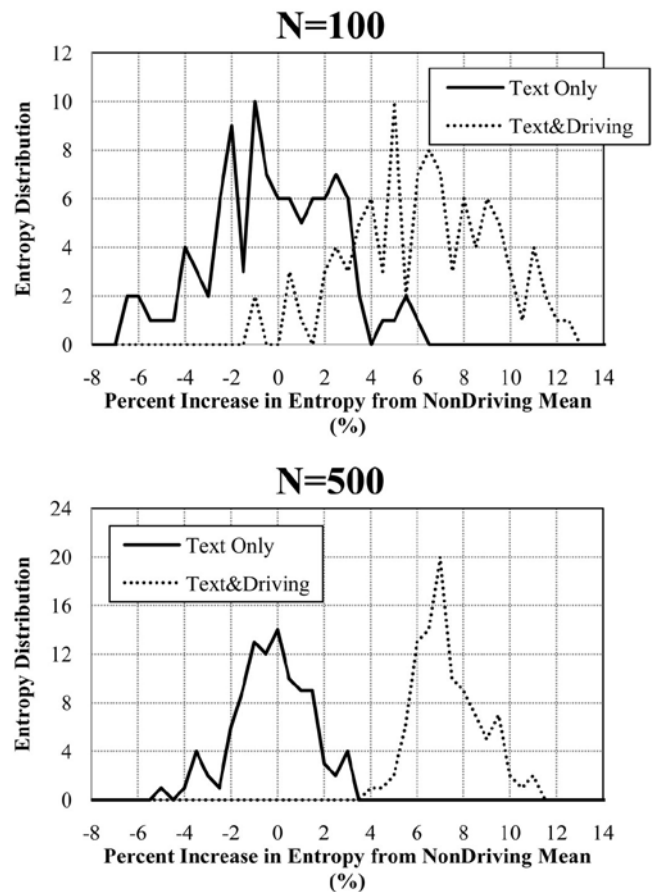


Fig. 2. Illustration of the increased separation of the entropy distributions as the number of keystrokes was increased from 100 to 500.

ROC curves similar to those of the other subjects. Fig. 3 illustrates the ROC curves for subject 245. In terms of differences in entropy, the two cases (texting versus texting while driving) are separable with thresholds of 2.5% to 7.5% increases over mean non-texting entropy. Table I contains data points from the ROC curves to illustrate the keystroke sampling to achieve a true positive rate of $\geq 99\%$. For purposes of discussion, an estimate of the “time to detection” is included. This estimate assumes a keystroke rate of 2 Hz, the average rate for the 10,115 keystrokes logged in the study. The results show that reliable discrimination can be obtained within several hundred keystrokes. This demonstrates excellent agreement with prior work (reporting error rates of around 2%) for authenticating the identity of keyboard user [14].

As mentioned earlier, the 70% false positive rate for subject #592 is explained by the relatively high attention level for texting while driving. This was accompanied by an elevated engagement in off-road and high-risk driving behavior that is unlikely to be replicated under on-road driving conditions.

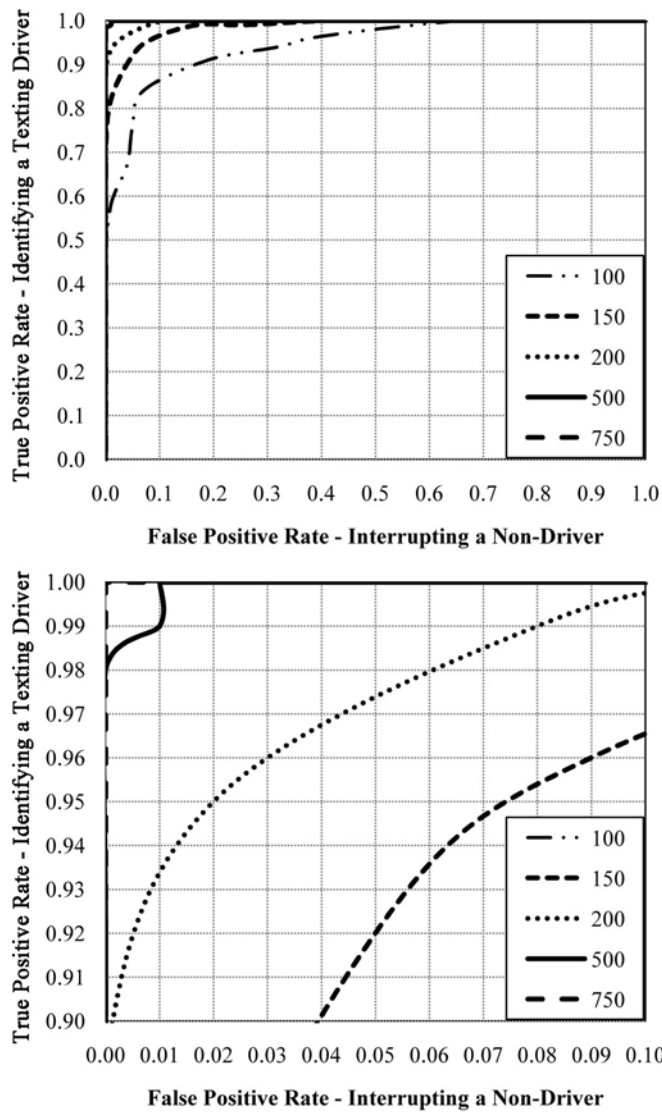


Fig. 3. ROC curves illustrating the fidelity of using keystroke entropy to distinguish a texting driver from a non-texting driver. Each curve represents a different keystroke sample size (n).

TABLE I. DATA EXTRACTED FROM THE ROC CURVES ILLUSTRATE THE REQUIRED KEYSTROKE SAMPLING TO ACHIEVE A TRUE POSITIVE RATE OF $\geq 99\%$ FOR ALL SUBJECTS

Subject #	Keystrokes Sampled (n)	Estimate of Time to Detection (minutes)	True Pos. (%)	False Pos. (%)
369	100	0.8	> 99	< 1
281	100	0.8	> 99	< 1
245	500	4.2	> 99	< 1
473	500	4.2	> 99	< 1
750	500	4.2	> 99	< 1
592	750	6.3	> 99	~70

The proposed concept is compatible with existing device operating systems and leverages GPS vehicle signatures to avoid nuisance false positives. Incorporating GPS signature filters to screen texting data from devices that are not being transported will further increase the reliability. In cases where the device is being transported during texting, the

mode of transport could be informed by the GPS signature (e.g., automobile, bus, train, ship, etc.). This knowledge can be used to assess relative risk scenarios and reduce the likelihood of nuisance (false positives) for vehicle passenger. Table II illustrates such a logic filter. S represents an appropriate GPS displacement signature parameter that reflects the likelihood that the device and user are occupants of a particular type of motor vehicle. If S is below some threshold, the state remains 0. If S exceeds the threshold and E is below a critical threshold, the state remains 0. This would be the case for a vehicle passenger. An additional level of reliability can be achieved by taking into account the type of vehicle. For instance, the likelihood of the user being a passenger for a bus displacement signature is much greater than the likelihood of being a passenger for an automobile signature. A distracted driving state of 1 is realized when both S and E exceed their critical thresholds. Otherwise no mitigation action is taken thus reducing the likelihood that a passenger's texting activity would be inappropriately interrupted.

TABLE II. GPS STATE FILTER FOR TAKING A MITIGATION ACTION. A STATE OF 1 TRIGGERS ACTIVATION AND A STATE OF 0 RESULTS IN NO ACTION.

	$E > E_{\text{threshold}}$	$E < E_{\text{threshold}}$
$S < S_{\text{threshold}}$	0	0
$S > S_{\text{threshold}}$	1	0

V. DISCUSSION

This study demonstrates that cell phones can autonomously, rapidly, and reliably detect driver distraction, by quantifying and evaluating changes in the device user's keystroke dynamics. This technique may provide a significant tool in addressing the growing problem of distracted driving within our nation's transportation system. The method provides several major advantages over the state-of-the-art. It addresses the "passenger problem," eliminates the need for a secondary in-vehicle device, requires no additional cell phone hardware, no exporting of the texting data, and does not require detailed knowledge of the linguistic information contained in the message. The latter is of particular interest in maintaining privacy of the texter. Although the preliminary classification method used scalar keystroke entropy, the method can be generalized to rich keystroke vector data (digraphs) and speech patterns. The approach is also applicable for alternative and evolving device inputs such as SWYPE texting. Vector fields, mathematically analogous to texting digraphs and SWYPE texting, have been used to characterize the intrinsic complexity of traffic in the airspace using entropy [15].

An important question regarding the outcomes of any study utilizing driving simulators is: To what extent can the results and conclusions be extended to on-road or naturalistic driving scenarios? An important outcome of the earlier work cited is that steering entropy for on-road trials was less than

that obtained using a driving simulator. This result is explained by a subject's rational reallocation of mental resources based on the difference in perceived risk between the two driving situations. In contrast to simulator driving, subjects focus more on driving and less on operating the cell phone while driving on-the-road. The implications are significant for anticipating evaluation of the current approach under naturalistic driving conditions. Increased inattention to the texting task should make it easier to detect distracted driving using the proposed classification method. This could translate to more rapid detection and/or higher reliability. This is very encouraging given the ROC curves presented above.

The utility of this approach is that it would enable engineering controls for mitigating distracted driving. The actual mitigating action could take on a range of forms graded for the particular situation, degree of distraction, and evolving legislative and liability issues. Examples of increasing levels of intervention are warning the device user, disabling texting functionality, switching to voice recognition texting, etc. Obviously the nature of the mitigation and the user groups will depend on a host of rapidly evolving market demands including, but not limited to, legislation and the liability landscape for carriers, automotive manufacturers, and the broader communications industry.

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