Are You Driving? Non-intrusive Driver Detection using Built-in Smartphone Sensors

Homin Park, DaeHan Ahn, Myounggyu Won, Sang H. Son, Taejoon Park
Daegu Gyeongbuk Institute of Science and Technology
Daegu, South Korea
{andrewpark, daehan, mgwon, son, tjpark}@dgist.ac.kr

ABSTRACT

In this work, we address a fundamental problem of distinguishing the driver from passengers using a fusion of embedded sensors (accelerometers, gyroscopes, microphones, and magnetic sensors) in a smart phone. Compared with the state-of-the-art solutions, a key property of our solution is non-intrusiveness, i.e., enabling accurate driver phone detection without relying on any particular situations, events, and dedicated hardware devices. Our system only utilizes naturally arising driver motions, i.e., sitting down sideways, closing the vehicle door, and starting the vehicle, to determine whether the user enters the vehicle from left or right and whether the user is seated in the front or rear seats.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; D.2.8 [**Software Engineering**]: Metrics—*complexity measures, performance measures*

Keywords

Driver Phone Detection; Driving Safety; Smartphone

1. INTRODUCTION

Any activities that could divert driver's attention away from the road endanger safety of the driver and others. Among various activities known to cause distractions, smartphone usage is by far the most alarming distraction since it requires visual, manual, and cognitive attentions from the driver. Based on the studies carried out in Virginia Tech Transportation Institute, sending or receiving a text takes driver's eyes off from the road for an average of 4.6 seconds. Assuming the vehicle is travelling at 55 mph, this leads to the equivalent of driving the length of an entire football field, blind [3]. As a result, statistics indicate that 15 to 25 percent of crashes at all levels are caused by distracted drivers [2] (mostly due to cell phone use), which leads to approximately 400,000 injuries per year. Efforts to prohibit drivers from using the phone while driving are already quite active. Forty-three states from U.S. have accepted the laws to ban texting while driving according to the National Highway Traffic Safety Administration [1], and such legislation is becoming critical world-wide. In the research domain, a variety of techniques have been developed to detect the driver's phone usage [10][4][5]. However, the state-of-the-art solutions often rely on particular situations (e.g., a phone in a pocket [4]) and events (e.g., driving over a bump [4], making a number of turns [10]). Some solutions are activated only when the driver is about to use the phone [5], which is not suitable for many driving safety applications.

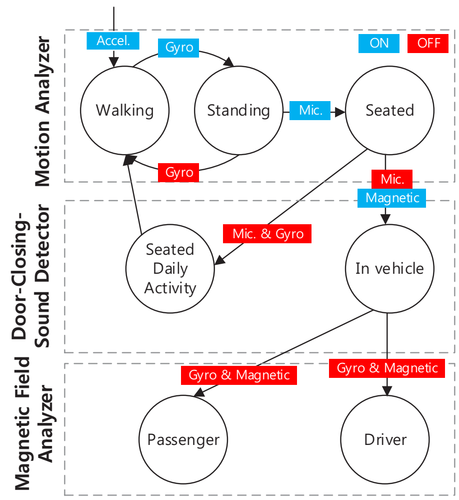


Figure 1: An overview of proposed system

In this work, a *non-intrusive solution* is proposed to distinguish the driver phone from passenger phones. A salient aspect of our proposed solution is that it requires neither additional dedicated hardware devices, nor any particular events and actions. Multiple built-in sensors, i.e. accelerometer, gyroscope, microphone, and magnetic sensors are effectively fused together to enable the detection leveraging only natural and indispensable driver actions – approaching the vehicle, standing still while opening the door, sitting down sideways, closing the vehicle door, and starting the vehicle, thus allowing for seamless system operations. Our proposed solution can be used with various driving safety applications which might suppress incoming and outgoing messages of the driver's phone, or activate voice recognition systems such as Siri or S-Voice.

MobiCom'14, September 7-11, 2014, Maui, Hawaii, USA.
ACM 978-1-4503-2783-1/14/09.
http://dx.doi.org/10.1145/2639108.2642896.

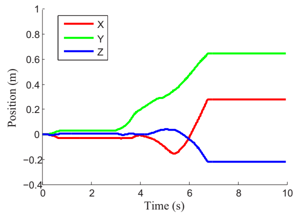


Figure 2: Relative Position

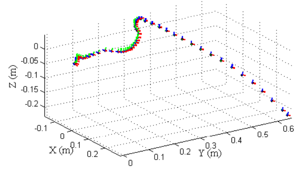
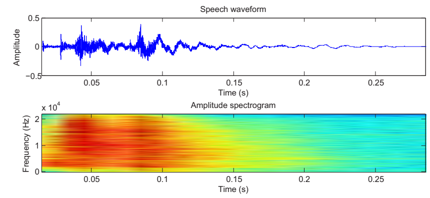
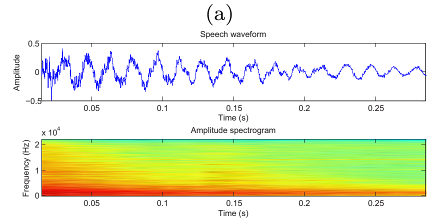


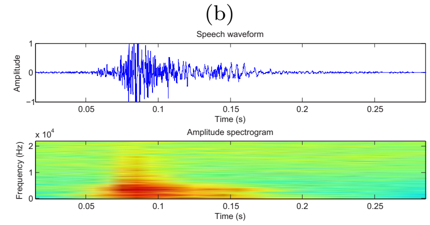
Figure 3: 3D Representation



(a)



(b)



(c)

Figure 4: Sound analysis for (a) lab door (b) bathroom door (c) vehicle door

2. SYSTEM DESIGN

The proposed system consists of three main components: Motion Analyzer (MA), Door-closing-sound Detector (DD), and Magnetic Field Analyzer (MFA). A component diagram of our system is shown in Figure 1 in which the components have states; and the state transitions are made when key events are captured using the sensors that are turned on at the given state. As illustrated, MA uses accelerometer and gyroscope sensors to classify walking, standing, and sitting down states. When the user is sitting down, the trajectory of given motion is captured, and will be used to identify the direction of vehicle entrance. Once the system concludes a user have been seated in the vehicle, microphones will be turned on to detect the vehicle-door-closing sound, which distinguishes daily sitting motions from entering a vehicle. After vehicle entrance is confirmed with vehicle-door-closing sound, the proposed system determines whether the user has entered the vehicle from the left or right by analyzing the direction of vehicle movements and the sitting down motion trajectories. MFA then comes into play to determine whether the user is seated in the front or back using magnetic sensors. With classified direction of vehicle entrance and seated location, our system determines whether the user is a driver or not. The details of each component are presented in the following subsections.

2.1 Motion Analyzer

MA uses the accelerometer and gyroscope to detect the sitting motion. An immediately faced challenge is that the gyroscope consumes too much energy, which makes it difficult to keep this sensor turned on. Thus, it is important to activate the gyroscope only when necessary. A key idea to address such challenge is that the gyroscope is activated only when a standing motion is detected (i.e., using the accelerometer) leveraging the fact that a standing motion is momentarily accompanied before the sitting motion. Once the gyroscope is turned on, the accelerometer readings are converted into absolute coordinates to capture the motion trajectories as shown Figures 2 and 3. As illustrated in Figure 2, a user was sitting down shortly after one second, which resulted in significant sensor reading changes in all 3 axes. Such accelerometer readings can be interpreted as a trajectory shown in Figure 3. The trajectory information is then fed to a classifier to determine whether given motion is sitting down or not. When the sitting motion is detected and the vehicle starts to move forward, the trajectory information is used to determine whether the user has entered a vehicle from left or right. Assuming the positive x-axis is the direction of vehicle movement, trajectory illustrated in Figure 3 leads us to conclude that the user have entered a vehicle from the right.

2.2 Door-closing-sound Detector

When the driver is seated, the next natural activity that the driver typically performs is closing the vehicle door. To detect the sound, DD turns on the microphone and starts to capture the sounds frame by frame. We leverage the fact that vehicle-door-closing sound has distinctive characteristics allowing for relatively easy sound classification. Vehicle doors are carefully designed to provide profound and reliable door-closing sound because it is one of the important factors affecting consumer's first impression [7]. Figure 4 illustrates distinctive acoustic signal characteristics of various types of door closing sounds. While other sounds consist of a wide range of frequencies that are strong enough to be audible, the frequency contents of vehicle-door-closing sound are concentrated in the low frequency range. In addition, vehicle-door-closing-sound signals tend to decay much quicker than the others. With such distinctive characteristics, we adopt the one-class classifier [9] to detect and differentiate the vehicle-door-closing sound from all kinds of other sounds that can be monitored during daily activities involving sitting motion. For the classification processes, each sound frame is analyzed to create a feature vector that contains chosen acoustic characteristics including – Short Time Energy, Fast Fourier Transform, Filterbank Energy, and Mel-frequency [6]. Such feature vector is used to generate aforementioned classifier, and to detect the vehicle-door-closing sound.

2.3 Magnetic Field Analyzer

Once the user is concluded to be in a vehicle with a specific direction of entrance, MFA now determines whether the phone is in the front or rear seats. Figure 5 and 6 illustrate that the rate of MF change (ROMFC) from the front

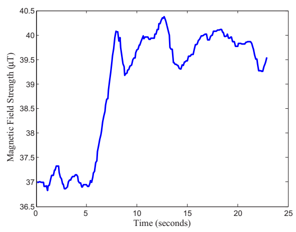


Figure 5: MF of front seat

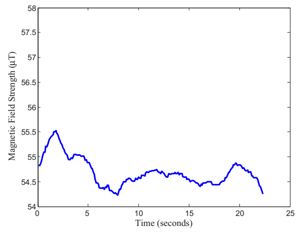


Figure 6: MF of rear seat

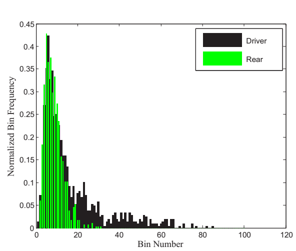


Figure 7: Normalized bin frequency graph for front and rear seats

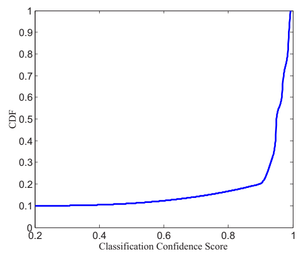


Figure 8: CDF of sound classification confidence scores

seat is much greater than that of rear, while overall MF strength from the front might be weaker. Such phenomenon is well expected since electronic and mechanical devices are installed and used around the front than the rear. In addition, we found that such overall MF reading difference between front and rear is attributed to the environmental factors, including orientation of the phone, location of the vehicle, and individual vehicle characteristics. Although the MF strength value itself does not distinguish the front from the rear, the ROMFC can be used to yield meaningful information.

To determine whether the user has been seated in the front or not, we compute the ROMFC for each time window, and generate a bin-based frequency histogram. Such histogram is generated by dividing the range of ROMFC values into n bins where each bin consists of dedicated sub-range of ROMFC values. For our work, we divided the range into 100 bins. With every ROMFC value computed, we identify the matching bin and increment the frequencies. Once frequency histogram is generated, given values are normalized as shown in Figure 7. Histogram from the driver (front) seat shows a long-tailed distribution while the rear seat shows a bell-shaped distribution concentrated on the left corner. With incoming data that needs to be classified, we create a corresponding bin-based frequency histogram, and apply the Earth Mover's Distance [8] to identify the similarity with reference histograms. The similarity indicate whether the incoming MF readings are from the driver (front) or rear seats of the vehicle.

3. PRELIMINARY RESULTS

Some preliminary experimental results are presented. Results for the fully integrated system are left as our future work. We first measured the accuracy of detecting sitting in vehicle which involves MA and DD. As Table 1 shows, sitting motions from daily activities were detected with accuracy of 100%, while the accuracy for detecting the event

Table 1: Accuracy of Detecting the Sitting Motion

	Sitting Event	
Detected	In Vehicle	From Daily Activity
In Vehicle	97%	3%
From Daily Activity	-	100%

Table 2: Accuracy of MFA

	Phone Location	
Detected	Front	Rear
Front	98%	2%
Rear	-	100%

of sitting in the vehicle had some small errors of ~3%, which is possibly attributed to some inaccuracy for detecting the door-closing sound. Figure 8 depicts the Cumulative Distributed Function (CDF) of sound classification confidence scores. It shows that DD has an average of 95.83% classification confidence. Finally, Table 2 displays the detection accuracy for MFA, i.e., determining whether the phone is in the front or in the back of the vehicle. The accuracy was measured with VW Jetta, and as shown, it has an accuracy of about 98%. We leave the measurements with various kinds of vehicle models as future work.

Acknowledgment

This research was supported in part by the DGIST R&D Program of MSIP of Korea (CPS Global Center) and the Global Research Laboratory Program through NRF funded by MSIP of Korea (2013K1A1A2A02078326).

4. REFERENCES

[1] Distracted driving laws. `http://www.ghsa.org/html/stateinfo/laws/cellphone_laws.html`.

[2] Governors highway safety association. `http://www.ghsa.org/html/issues/distraction/index.html`.

[3] Official website for distracted driving. `http://www.distraction.gov/content/get-the-facts/facts-and-statistics.html`.

[4] C. Bo, X. Jian, X.-Y. Li, X. Mao, Y. Wang, and F. Li. You're driving and texting: detecting drivers using personal smart phones by leveraging inertial sensors. In *Proc. of MobiCom*, 2013.

[5] J. G. Elias. Driver handheld computing device lock-out, Apr. 22 2014. US Patent 8,706,143.

[6] Y. Guo and M. Hazas. Localising speech, footsteps and other sounds using resource-constrained devices. In *Proc. of IPSN*, 2011.

[7] E. Parizet, E. Guyader, and V. Nosulenko. Analysis of car door closing sound quality. *Applied Acoustics*, 69(1):12–22, 2008.

[8] Y. Rubner, C. Tomasi, and L. J. Guibas. The earth mover's distance as a metric for image retrieval. *International Journal of Computer Vision*, 40(2):99–121, 2000.

[9] D. M. Tax and R. P. Duin. Support vector data description. *Machine learning*, 54(1):45–66, 2004.

[10] Y. Wang, J. Yang, H. Liu, Y. Chen, M. Gruteser, and R. P. Martin. Sensing vehicle dynamics for determining driver phone use. In *Proc. of MobiSys*, 2013.