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Improving Driving Safety by Preventing Driver Distraction

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***Abstract*—This paper presents a novel system designed to detect and prevent driver distraction caused by the use of mobile phones while driving. The Phone-Locating-Unit (PLU) is based on a multi-modal approach that exploits inputs from several sensors. In-cabin cellular activity and Inertial Measurement Unit (IMU) information is supplemented by additional information on wireless in-cabin activity. The challenges we faced when designing the PLU, compared to classical RSSI systems is the near-field multipath impediment, and the small number of antennas in the vehicle. On the other hand, only a binary decision is required, whether the emitter is used by the driver or not. The system also employs Neural Networks (NN) and Machine-Learning (ML) to fuse the IMU information. We detail the propagation model and in-cabin field measurements and show that the PLU can detect and prevent drivers from being distracted without any prior knowledge of the number of smartphones, their in-cabin locations, or the number of passengers in the vehicle. We demonstrate the effectiveness of the approach to accurately detect in cabin cellular activity, with a clear distinction between driver and passenger activity, despite the unique and challenging characteristics of the in-cabin propagation channel.**

***Index Terms*—Activity recognition, distracted-driver, driving-style, insurance telematics, intelligent vehicles, multiple antennas, road safety, smartphone**

I. Introduction

One of the most revolutionary changes of this century has been the incorporation of mobiles and specifically smartphones in daily life regardless of geographies, age groups, socioeconomic status and cultural background. In almost every corner of the world there are smartphones. Although these electronic devices have enormous advantages, we are guilty of believing that the only drawback is related to screen time per day, while dismissing the dangers of vehicular use of smartphones by drivers.

Years prior to the current viral pandemic, the world has been dealing with a technological pandemic with equally deadly consequences: distracted driving caused by the use of mobile phones while driving. This affects every country, every culture and is sadly increasing by the minute. As more functionalities are incorporated to smartphones and people feel the urge to be connected 24/7, the risk has snowballed and more victims are reported every year. In the US alone, each year more than 400,000 people are injured and more than 3,000 people are killed in motor vehicle crashes involving distracted drivers, making up nearly 10% of all fatal crashes [1], and 25% of all car crashes in the US involved the use of a cell phone [2]. Given the number of drivers worldwide, the rate of near misses due to mobile usage while driving is estimated to be astronomical. Despite the shocking statistics in apparently avoidable circumstances, few effective strategies for minimizing the impact of this problem have been put forward.

Even with significant advances in communication technologies, we are still at the mercy of driver compliance and awareness of the risks involved..

We consider a multi-modal system, where the main source is the cellular activity, and other information is obtained from the Inertial Measurement Unit (IMU) including the system sensors (e.g., [3]), such as the accelerometer and gyroscope. We also harness NN and ML tools to fuze the data accordingly.

Besides safely, the information on the cellular activities is used for *connected cooperative vehicle environment* in autonomous vehicles (e.g., [4]). This has been attracting considerable interest from OEMs and researchers for entertainment and driving environments.

An effective system should not depend on the willingness of the driver to collaborate, while at the same time, should avoid infringing on privacy. Thus, the PLU system should not be in the form of a mobile app installation. However, we also propose a friendly protection driver app, without any data breaches or reading of the data, and show that such app brings the accuracy of distraction prevention up to 100%.

In-cabin propagation channel is challenging [5] – [9]. Wang et al. [5] paved the way for in-vehicle localization, however, their system only performs well if the smartphone devices are static, and requires an acceleration measurement from a reference device inside the car. In addition, this algorithm takes time to converge, and cannot work in real time.

Recently, Ahmad el al. [8] surveyed categories of non-intrusive smartphone-based identification approaches. Traditional methods are based on WiFi detection. The channel propagation of WiFi devices at 2.435 GHz to determine the unique characteristics of the in-cabin channel were analyzed [7]. Other works have considered various numerical simulations and ray tracing models (e.g., refer to [7]).

This paper extends the previous work in [7] and presents a novel system that works in real-time to detect and classify in-cabin cellular activity, and detects the driver even without

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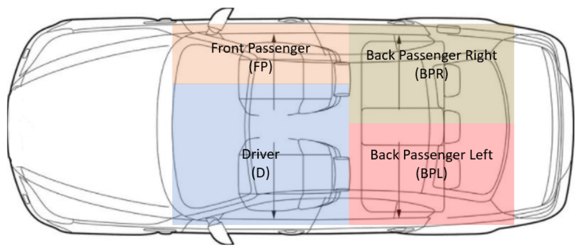

Fig. 1. The Phone-Locating-Unit (PLU) system requires the placement of few concealed antennas within the car. The PLU needs to detect and classify the smartphone in one of the 4 quarters: driver (D), front-passenger (FP), back–passenger-left (BPL) and back–passenger-right (BPR).

collecting information from his / her smartphone. The design of the system is oriented toward a practical installation without affecting the experience of the driver or the passengers.

The remainder of this paper is organized as follows. Section II presents the system model, Section III presents the measurement platform and results, and conclusions are provided in Section IV.

II. System Model

In this section we present the fundamental characteristics of the in-cabin channel propagation and the information received from IMU sensors that are used for multi-modal processing. We use a Received-Signal-Strength-Indicator (RSSI) algorithm to detect and locate the cellular activity in the car. In parallel, we use the IMU sensor to compute the most likely driving and smartphone pose mode.

The next section confirms the theoretical models developed in this section to describe the channel through measurements.

A. In-cabin channel propagation

The parameters to be estimated are the coordinates of the smartphone which is assumed to be transmitting

$$\mathbf{p}_t = [x_t, y_t, z_t]^T \tag{1}$$

while the locations of receivers are known. The location of the i-th receive sensor is

$$\mathbf{p}_i = [x_i, y_i, z_i]^T. \tag{2}$$

We denote the distance between the target and the i-th receive sensor by r_i. These distances are given by

$$\begin{aligned} r_i &= \|\mathbf{p}_t - \mathbf{p}_i\| \\ &= \sqrt{(x_t - x_i)^2 + (y_t - y_i)^2 + (z_t - z_i)^2}. \end{aligned} \tag{3}$$

where $\|\mathbf{x}\|$ is the norm of vector $\mathbf{x}$. The delay (travel time) of the signal between the smartphone to the i-th receive sensor is:

$$\tau_i \triangleq \frac{r_i}{c} \tag{4}$$

where r_i is the distance given in (3) and c is the speed of light.

In the following, we describe the analog representation of the received signal, at the i-th receiver which is given by[1]:

$$\begin{aligned} y_i(t) \approx \sqrt{P} \cdot r_i^{-\alpha/2} s(t-\tau_i) \cdot e^{j2\pi f_{\mathrm{d},i} t} \cdot e^{-j2\pi f_c \tau_i} * h_i(t) \\ + w_i(t) \end{aligned} \tag{5}$$

where P is the transmitter effective radiated power of the smartphone and $h_i(t)$ is the multipath impulse response between the transmitter and the i-th receiver (as detailed in (6)). The path loss parameter satisfies $\alpha > 3$. The *Doppler frequency shift*, $f_{\mathrm{d},i}$, is due to the transmitter velocity. The terms $e^{j2\pi f_{\mathrm{d},i} t}$ and $e^{-j2\pi f_c \tau_i}$ stand for the Doppler and the delay (range), respectively. For simplicity, we assume that the noise, $w_i(t)$, follows a standard complex normal distribution, $\mathcal{CN}(0,1)$, and is independent of $s(t)$.

In our scenario, the environment of a car cabin, the reflection due to hitting the rear door has at most a 3 m round trip distance, which is equivalent to a delay of 10 ns.

We model the multipath by

$$\begin{aligned} h_i(t) = \delta(t) \\ + \sum_{m=1}^{M} a_{i,m} \cdot \delta(t - \tfrac{d_{i,m}}{c}) e^{-jk \cdot d_{i,m}} e^{-j2\pi f_{\mathrm{d},i,m} \cdot t} \end{aligned} \tag{6}$$

where M denotes the number of multipath components. We used $d_{i,m}$ to denote the *incremental distance*[2] of the m-th multipath at the i-th receive sensor, $k \triangleq 2\pi f_c / c$ is the wave number. We denote by $f_{\mathrm{d},i,m}$ the relative Doppler of the i-th sensor at the m-th multipath, which is bounded by $f_{\mathrm{d},i,m} = f_c \cdot \frac{v}{c} \approx f_c \cdot \frac{1}{c} < 10$ Hz since we assume that the velocity of the smartphone movement is at most $v < 1$ m/s, and the carrier frequency satisfies $f_c < 4$ GHz the most common uplink cellular used in vehicles.

To detect and classify the in-vehicle cellular activity, we use the RSSI algorithm. To the best of our knowledge, we are the first to consider the hybrid RSSI approach in a near field scenario for the detection of in-vehicle cellular activity. After detecting the cellular activity, the RSSI-based algorithm classifies the location of the smartphone to one of 4 quarters (see Fig. 1): driver (D), front-passenger (FP), back–passenger-left (BPL) or back–passenger-right (BPR).

B. IMU Multi-Modal Fusion

To increase the accuracy of the system, we incorporate information from IMU sensors. To that end, we consider two cases. The first involves an "unfriendly" driver who does not provide access to his/her smartphone, where the in-cabin cellular activity will be detected by using the receiving antennas in the PLU system and where the IMU information will be provided to the PLU (the PLU contains IMU sensors).

By contrast, a "friendly" driver allows access to his/her smartphone, which provides valuable information about the

[1] This formula is valid when the distance is larger than 3-4 times the wavelength. We consider a minimal frequency of 700 MHz. The wavelength if given by $\lambda = c/f$, so in this case, $\lambda(700\text{MHz}) \approx 43$ cm.

[2] The incremental distance is equivalent to the propagation delay relative to the first arrival at the receiving antenna for a waveform coming from the source transmitter.

activity from the smartphone IMU (e.g., [3]) and additional information such as GPS speed API, which increases the accuracy. We relate this to human-activity-recognition (HAR) (e.g., [10] and references therein), or, in our case *driver activity recognition*, that aims to identify the actions and different poses of the driver related to using the smartphone. We capture the 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50 Hz using the embedded accelerometer and gyroscope of the smartphone.

Since the accelerometer and gyroscope measurements are noisy, we adopt low pass and second-order filtering. We use both machine and deep learning algorithms. For ML, we use a logistic regression classifier, that produces good results and accuracy with threshold learning that is faster and simpler. In the case where the driver provides access to his/her smartphone, we filter and extract the features from the IMU sensors in the smartphone and GPS speed. For the deep-learning tool, we use Long-Short-Term-Memory[3] (LSTM) which has been applied to the HAR problem and provides good results (e.g., [11]).

The estimation process can be divided into two phases, namely offline and online. During the offline phase, feature extraction is conducted to integrate the sensor data into diversified features to train the LSTM model. During the online phase, the system transforms the testing data into feature vectors, and feeds these data to the previously trained LSTM model.

III. Measurement Platform And Results

This section presents the performance effectiveness of the Phone-Locating-Unit (PLU) system. We present in-cabin field measurements and show the effectiveness of the PLU system to detect distracted drivers without any prior knowledge of the number of smartphones, the in-cabin smartphone locations or the number of passengers within the vehicle. The physical platform we used was a Hyundai Ioniq, a typical private car which has an average cabin size. Clearly, a bigger vehicle, like car, provides better results.

In our system we used patch antennas that can be mounted on a flat surface, and radiate perpendicular to the antenna surface. Our system is highly agnostic to the polarization of the antennas and hence can be neglected. We concealed the (passive) receiving antennas within the vehicle so that: 1) the driver does not know the location of the antennas, 2) they can serve to provide smooth measurements over time. In practice, we tried various sets of combinations and locations for $\{2, 3, ..., 6\}$ antennas that can perform for years after installation and will not affect the driver or passenger experience.

We performed tests to demonstrate the performance of the PLU system. We started solely with RSSI knowledge which considers only the wireless propagation without the driver's collaboration. The results constitute the performance benchmark of our system before collecting additional knowledge. This information is denoted as *RSSI-based*.

[3]An LSTM has the architecture of a recurrent neural network (RNN).

(a) (b)

Fig. 2. The challenging positions of the transmitting smartphone device is placed on (a) Driver's right hand (DRH), (b) Gear.

Next, we added the IMU information by the PLU, and extracted the features. This provided an additional performance gain and reduced alerts in the cases of vehicle statics. This information, together with the RSSI-based information is denoted as: + *PLU-IMU*.

Last, we added the complementary information from the smartphone IMU sensors, and the GPS speed API. This information is authorized by the driver. This information enables the system to achieve the highest score. This smartphone (SP) information, together with the RSSI-based plus PLU-IMU information is denoted as: + *SP-IMU*.

We present results for the following positions of the phone: 1) Driver's left hand (DLH), 2) Driver's dashboard left (DDL), 3) Driver's right hand (DRH), 4) Gear, 5) Front Passenger (FP), 6) Back passenger left (BPL), 7) Back passenger right (BPR). Please refer to Fig. 2 to illustrate the DRH and Gear positions.

We used the popular models Samsung S21, Samsung Galaxy S10 and iPhone 12. In all, we tested the activity of the driver / passengers texting and holding the smartphone in the 7 positions, in driving and standing states. In the non-driver states, the driver was idle (i.e., did not used his/her smartphone) and only the passengers were engaged. We averaged the results over all the smartphone models and states per position.

In all positions and the states, the detection probability was 1, as a result of the scanning speed of the spectrum. We used offline tests to calibrate weights and thresholds of the algorithms, that control the system's bias. For example, a selection of weights and thresholds can provide great classification of the driver's positions, while pays less attention to the accuracy of the front passenger's position. We chose to provide general classification while reducing the false positive.

Table I presents the results of the position versus the information provided to the PLU system. As can be seen, the more information given, the better the results. Note that for 2 positions, the DRH and the Gear, the classification, was ambiguous since these positions are on the border between the driver and the front passenger. Nevertheless, in the other positions, the classification rate was very high.

	DLH	DDL	DRH	Gear	FP	BPL	BPR
RSSI-based	96.1%	92.8%	85%	82%	94.7%	97.9%	97.2%
+ PLU-IMU	96.9%	93.2%	86.1%	83.5%	96.1%	98.2%	98%
+ SP-IMU	100%	100%	98.4%	94.2%	100%	100%	100%

TABLE I
CLASSIFICATION RESULTS BASED ON THE FOLLOWING POSITIONS: 1) DRIVER'S LEFT HAND (DLH), 2) DRIVER'S DASHBOARD LEFT (DDL), 3) DRIVER'S RIGHT HAND (DRH), 4) GEAR, 5) FRONT PASSENGER (FP), 6) BACK PASSENGER LEFT (BPL), 7) BACK PASSENGER RIGHT (BPR).

IV. CONCLUSIONS

In this paper, we presented the PLU system which is designed to detect and prevent driver distraction caused by the use of mobile phones while driving. The PLU is a multi modal system that analyzes in-cabin cellular activity and IMU information. We employed deep learning and ML to fuze the IMU information. We demonstrated the effectiveness of the PLU to accurately detect and classify in-cabin cellular activity, with a clear distinction between driver and passenger activity, despite the challenging in-cabin propagation channel.

Future research will consider a hybrid RSSI-AoA algorithm (e.g., [12]) for better differentiation in the challenging cases of DRH and gear, and to achieve better performance without the driver's cooperation. We are in validation stages of this novel algorithm, which will appear in the full journal version.

REFERENCES

[1] "NHTSA Distracted-Driving," https://www.nhtsa.gov/risky-driving/distracted-driving, [Online].
[2] "Texting and Driving Statistics," https://carsurance.net/blog/texting-and-driving-statistics/, [Online].
[3] S. Gelmini, S. C. Strada, M. Tanelli, S. M. Savaresi, and V. Biase, "Online assessment of driving riskiness via smartphone-based inertial measurements," *IEEE Transactions on Intelligent Transportation Systems*, 2020.
[4] J. He, Z. Tang, X. Fu, S. Leng, F. Wu, K. Huang, J. Huang, J. Zhang, Y. Zhang, A. Radford *et al.*, "Cooperative connected autonomous vehicles (cav): research, applications and challenges," in *2019 IEEE 27th International Conference on Network Protocols (ICNP)*. IEEE, 2019, pp. 1–6.
[5] Y. Wang, J. Yang, H. Liu, Y. Chen, M. Gruteser, and R. P. Martin, "Sensing vehicle dynamics for determining driver phone use," in *Proceeding of the 11th annual international conference on Mobile systems, applications, and services*, 2013, pp. 41–54.
[6] Z. He, J. Cao, X. Liu, and S. Tang, "Who sits where? infrastructure-free in-vehicle cooperative positioning via smartphones," *Sensors*, vol. 14, no. 7, pp. 11 605–11 628, 2014.
[7] L. Cheng, J. Casazza, J. Grace, F. Bai, and D. D. Stancil, "Channel propagation measurement and modeling for vehicular in-cabin Wi-Fi networks," *IEEE Transactions on Antennas and Propagation*, vol. 64, no. 12, pp. 5424–5435, 2016.
[8] B. I. Ahmad, P. M. Langdon, J. Liang, S. J. Godsill, M. Delgado, and T. Popham, "Driver and passenger identification from smartphone data," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 4, pp. 1278–1288, 2018.
[9] G. Johnson and R. Rajamani, "Smartphone localization inside a moving car for prevention of distracted driving," *Vehicle system dynamics*, 2019.
[10] S. Porwal, S. Singh, N. Yadav, and D. Garg, "Review paper of human activity recognition using smartphone," in *2021 5th International Conference on Trends in Electronics and Informatics (ICOEI)*. IEEE, 2021, pp. 939–946.
[11] N. Kadri, A. Ellouze, and M. Ksantini, "Recommendation system for human physical activities using smartphones," in *2020 2nd International Conference on Computer and Information Sciences (ICCIS)*. IEEE, 2020, pp. 1–4.
[12] K.-J. Baik, S. Lee, and B.-J. Jang, "Hybrid RSSI-AoA positioning system with single time-modulated array receiver for LoRa IoT," in *2018 48th European Microwave Conference (EuMC)*. IEEE, 2018, pp. 1133–1136.