

Distracted Driving Detection Utilizing Wearable-based Bluetooth

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Abstract—Distracted driving has become a serious problem for driving safety with the growing number of fatalities each year. Existing mobile and wearable based distracted driving detection systems have shortcomings of requiring additional hardware or explicit user involvement for training. Moreover, the excessive use of various sensors can cause fast battery drain and overheating which is less practical for daily use. In this work, we present a wearable-based distracted driving detection system leverages Bluetooth. Our system exploits already in-vehicle Bluetooth compatible devices to track the driver's hand position and infer unsafe driving behaviors. The proposed system doesn't require explicit user cooperative for training, and involves low energy consumption. Experiments show our system can achieve over 95% distracted driving detection accuracy under various scenarios.

Index Terms—Bluetooth, driving safety, wearable, mobile sensing

I. INTRODUCTION

In the recent years, much effort had been done to improve driving safety, yet a large number of accidents at various scales still occurred which lead to serious injuries or casualties as well as economic loss [1]. Many of the accidents are caused by distracted driving behavior which is defined as doing other activities that takes the driver's attention away from driving [2]. A few examples of distracted driving behaviors include: using mobile devices, eating/drinking, operating onboard systems, searching in-vehicle items, and applying makeup/grooming. Recent studies show distracted driving have become one of the fast-growing factors that lead to fatal accidents and serious injuries [3]. Every year, distracted driving causes about 2.5 million car crashes in US alone. In 2019, it cause over 3000 fatalities that account for over 9% of the total fatal crashes [4].

Many policies and infrastructure support have been proposed to mitigate the risk of distracted driving. For example, several states have passed laws to prohibit all drivers from using handheld cellphones while driving [5]. Moreover, in different areas, billboards or signs have been setup around the roadway to remind driver of dangerous distracted driving behavior and its consequences [6]. Meanwhile much research effort have been dedicated to develop different techniques that can detect distracted driving behavior. Traditionally, computer vision based approaches utilize cameras to achieve unsafe gesture recognition of drivers [7]. But such a solution cannot work

under poor lighting conditions or none-line-of-sight(NLOS) scenarios which greatly limit its applicable scenarios. Additionally, it often involves user privacy concerns.

With the recent advancement of wearable technologies, several systems [8], [9] have been proposed to achieve driver gesture recognition using motion sensors embedded in wearable devices. However, the sensory data extracted from the wearable device contains the vehicle's motion which can be difficult to separate. Similar system proposed by Karatas *et al.* [10] can achieve driver gesture recognition by separating the vehicle's motion data from the wearable device. It is done by utilizing the smartphone motion sensor that mainly contain vehicle's motion information. However, because of the hardware limitation on mobile and wearable devices, such system require continuous calibration to maintain accuracy [11]. Moreover, the excessive use of various sensors can cause fast battery drain and possible device overheating problems [12].

Another body of work leverage acoustic or RF signals to recognize driver gestures. CARIN [13] utilized RF-based technology to recognize activity of driver in the presence of passenger interference. V2iFi [14] can achieve in-vehicle vital sign monitoring using Channel State Information data. Those systems can achieve high detection accuracy but require additional hardware installation and extensive training. Steer-Track, DriverSonar and D3-Guard [15]–[17] utilize acoustic signals emitted and captured by smartphone to track the driver's gestures. However, those systems require constant profile/model update once the placement of the phone changes and explicit user involvement during the training phase which can be less practical for daily use scenarios.

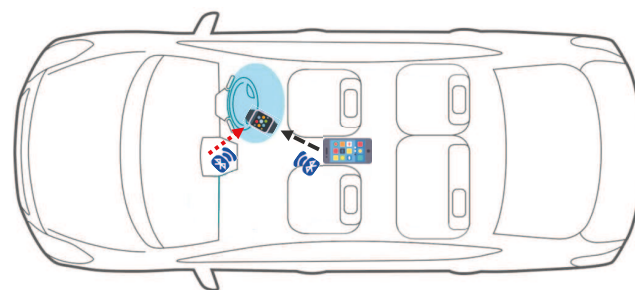


Fig. 1. Illustration of the typical use case of our system.

In this paper, we propose a wearable-based distracted driving detection system utilizing Bluetooth. This work takes advantage of already in-vehicle Bluetooth compatible devices to infer unsafe driving behaviors. Using only the smartwatch Bluetooth probe signals, our system can achieve distracted driving behavior recognition by detecting if the driver's hand is on/off the steering wheel. It is done by sensing the hand position of the driver with respect to the steering wheel leveraging only Bluetooth probe signal and implicit user profile construction.

In particular, our system exploits a Bluetooth ranging approach that leverages wearable device along with in-vehicle Bluetooth compatible devices to infer the hand position with respect to the steering wheel. Although the basic Bluetooth based ranging techniques suffer from the uncertainty and low accuracy of position estimation due to the poor stability and small bandwidth of Bluetooth signal. Our system overcomes such shortcomings by utilizing multiple Bluetooth compatible devices within the vehicle which can reduce the uncertainty of the received signal and further improve the ranging accuracy. Additionally, our system leverages the time period where the vehicle pulls out of the park area for profile construction and update. Such an approach can achieve the training implicitly without user active cooperation or awareness.

Fig 1 illustrates the typical use case of our system (i.e., one driver where he/she carries his/her own smartphone). The key idea underlying our system is to perform Bluetooth ranging using multiple devices. The system will be triggered by the moving of the vehicle which can be inferred leveraging the smartphone motion sensors (e.g., accelerometer). Then, all the available Bluetooth compatible devices including onboard Bluetooth system and smartphones will probe the wearable device worn by the driver. The wearable device records the received signal strength indicator (RSSI) and processes the data to infer its current position. Instead of localizing the absolute position of the wearable device in 3D space which can be easily obscured by unknown processing delay and unstable Bluetooth signal, our system relies on the Bluetooth signals from multiple devices to infer the relative position of the driver's hand with respect to the steering wheel. Here, we define the hand placement on the surface of the steering wheel as a safe zone which is highlighted using the light blue color in Fig 1. For example, when the user uses mobile devices, the inferred position of the user's hand will be too far from the safe zone. If the user's hand does not return to the safe zone for a prolonged period of time (e.g., more than 3s), our system will deem the driver is conducting unsafe driving behaviors and alert the driver.

Different from existing solutions, our system does not require explicit user involvement in training and consumes much less battery power compared to other approaches, therefore can be easily adopted for daily usage. To evaluate the performance of our system, we conduct experiments in different road conditions and under various distracted driving behaviors. We also evaluate our system using different phone placements and various number of in-vehicle Bluetooth compatible devices. Experimental results show that our system is highly effective

in detecting distracted driving behaviors. The contribution of our work is summarized as follows:

- We propose a distracted driving detection system to improve driving safety by utilizing only Bluetooth of the wearable device.
- We utilize multiple in-vehicle Bluetooth compatible devices to further improve the accuracy and reduce the instability of Bluetooth ranging.
- We leverage the car backing out of the parking time period to achieve implicit user profile construction and update without user awareness.
- Our experimental results show that the proposed system can achieve over 95% distracted driving detection. Results also show that our system can work under different phone placement and various road conditions.

II. RELATED WORK

There are many research efforts that have been dedicated to enhance driving safety, especially for the distracted driving behaviors [18]–[20]. Existing driving safety systems can be divided into three categories: computer vision based systems, motion sensor based systems, RF and acoustic based systems.

Computer Vision based Systems. This category of work aims to sense the driver behavior utilizing cameras. For example, Zhang *et al.* [7] proposed a cellphone use behavior detection system utilizing a camera mounted above the dashboard. Such an approach can not work well under NLOS or poor lighting conditions. It also raises user privacy issues.

Motion Sensor based Systems. This body of work focuses on sensing the driver's hand gestures and inferring the dangerous driving behavior using motion sensors embedded in wearable devices. System proposed by Wang *et al.* [19] is one of the early works that uses motion sensors to distinguish driver from passenger for driving safety improvement. For instance, Safedrive [8] and Safewatch [9] achieve distracted driving detection using wrist-worn devices. However, the sensory data extracted from the wearable device contains the vehicle's motion which can be difficult to separate. System proposed by Karatas *et al.* [10], [10] can achieve driver gesture recognition by separating the vehicle's motion data from the wearable device. However, because of the hardware limitation on mobile and wearable devices, such systems require continuous calibration to maintain accuracy [11]. Thus, the motion sensor based approaches are not practical for everyday use.

Acoustic or RF based Systems This type of systems utilizes acoustic/RF signals to sense the user's gesture for driver behavior recognition. Systems proposed by Yang *et al.* [18], [20] are among the first work to use acoustic signals to detect driver phone use and improve driving safety. CARIN [13] can recognize activity of driver in the presence of passenger interference using Channel State Information. V2iFi [14] can achieve in-vehicle vital sign monitoring using similar techniques. However, those systems require additional hardware installation and extensive training to achieve high accuracy. On the other hand, SteerTrack, DriverSonar and D3-Guard [15]–[17] utilize inaudible acoustic signals emitted and

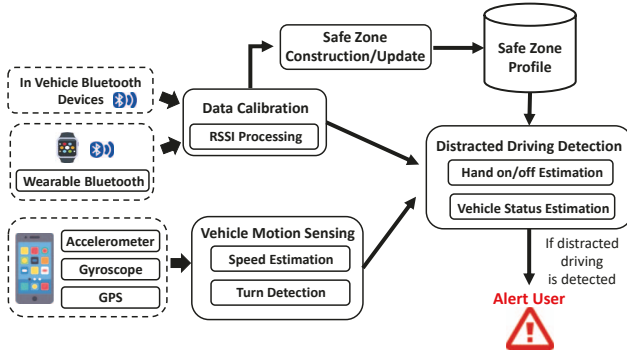


Fig. 2. Overview of the system flow.

captured by the smartphone to track the driver's hand gestures and infer driver's behavior. But those system can only work when smartphone is placed at the position where directly facing the driver and the excessive use of various sensors can cause fast battery drain and possible device overheating problems [12].

III. SYSTEM DESIGN

The basic idea of our system is to infer the driver's hand position with respect to the steering wheel leveraging Bluetooth RSSI from multiple devices in the vehicle during the driving period. Fig 2 shows the overview of our system. At first, our system will perform Bluetooth collection, in which all the available Bluetooth compatible devices in the vehicle(e.g., car Bluetooth, smartphone Bluetooth) continuously send out probe signals and the wearable devices worn by the user extract RSSI measurements from each received probe signal packet. For our system the default sampling frequency is set at 100Hz and the Bluetooth collection process will persist during the driving period. Note that it is possible to further improve the detection accuracy by increasing the sampling frequency.

As shown in Figure 2, our system consists of three major components: *Data Calibration*, *Vehicle Motion Sensing*, and *Distracted Driving Detection*. The collected Bluetooth measurements first go through *RSSI Processing* to mitigate the interferences and noises caused by hardware imperfection. This step is necessary because the channel propagation performance between signal transmitters and receivers fluctuates drastically during the transmission process. Such interference caused by fluctuation of the propagation is indeterminate and unpredictable even in a LOS environment [21]. Thus, it is difficult to achieve accurate Bluetooth ranging by simply applying raw Bluetooth RSSI. To resolve this issue, we leverage a Wavelet filter based approach to mitigate the noises and stabilize the RSSI value [22]. It is done by breaking the original signal into its wavelets with different frequencies then applying different levels of thresholds to mitigate the noises while maintaining the distance information. Meanwhile, our system also go through *Vehicle Motion Sensing* process that takes in motion sensor data and GPS information extracted from in-vehicle mobile devices and infer the current status of the vehicle (e.g, the current speed or if the vehicle is making a turn).

After the calibration process, our system will conduct safe zone construction and update utilizing the de-noised RSSI measurements. Unlike many existing wearable-based approaches that require explicit user involvement or active user cooperation for profile construction or update, we take advantage of the time period where the vehicle pull out of the parking area to conduct profile construction and update. In order to pull the vehicle out of parking area, the user's hand is usually on the steering wheel during that time period and our system leverage the RSSI measurements collected to construct or update the safe zone for that trip implicitly without user awareness. We can infer the duration of car pulling out of park area by leveraging the motion sensors and GPS information acquired from the previous step. For example, during this period, the car will go through a series of backing and turning motion which can be easily derived using the accelerometer, gyroscope and GPS data extracted from the mobile devices in vehicle. In general, it takes 10s to 30s to pull out of the parking area depends on the parking location and traffic which is more than enough to achieve safe zone construction or update for each trip. The processed Bluetooth RSSI measurements collected during the profile construction or update period will be used as safe zone data.

It is worth noticing our current system assume the placement of user's phone stay consistent during the process. However, there still exists possible scenarios where the user might pick up the phone and place it in a different position during the trip (e.g., check the phone when car is stopped and put it back when the car is in motion again). To handle this situation, we could use the phone's motion sensor data (i.e., accelerometer, gyroscope, and magnetometer) to infer the trajectory change of the phone movement and derive the new position of the phone or determine if the phone has been placed back to its original position. If not, our system can just rely on the car Bluetooth for distracted driving detection. We would like to incorporate this into future work that allows our system to handle additional phone position change scenario.

Next, our system will go through *Distracted Driving Detection* to determine if driver is conducting distracted driving behavior. To achieve that, we first utilize the results from *Vehicle Motion Sensing* process to determine the current vehicle motion status such as if the car is moving or making a turn. If the car is not in motion, then we assume the car is temporarily stopped at the traffic light or parked in the parking area. For both scenarios, there is no need to activate the detection process since distracted driving behaviors are only considered during the driving period. On the other hand, if the results from *Vehicle Motion Sensing* indicate the car is in motion, our system will go through *Hand on/off Estimation* process to determine if the driver's hand is off the steering wheel. In order to achieve that, we estimate relative position driver's hand with respect to the safe zone we construct from previous step. It is done by using one-class Support Vector Machine (SVM) based classification module. We choose the following features to characterize the safe zone: normalized standard deviation, the offset of signal strength, the median

absolute deviation, and the interquartile range. In the process of construct classification model. For the training, we took over 30 minutes data from real world driving scenario, which consists of eight participants keep their hands on the steering wheel while making turns or keeping static. The rest is used for testing and each user's data is used for his/her own training model.

Our system currently only uses empirically selected thresholds to achieve better detection accuracy leveraging existing data sets. This could potentially affect system performance especially when the proposed system is under the massive deployment scenarios. Additionally, we only use SVM as the classification module for distracted driving behavior detection which is highly depend on current data sets. Thus, we propose to utilize more sophisticated machine learning/deep learning techniques (e.g., CNN, RNN) to achieve better adaption with different data sets. We will explore this as our future work to improve the robustness and performance of the system under various scenarios.

IV. EVALUATION

A. Experiment Setup

Devices and Vehicles. We implement our system on a Moto 360 3rd Gen smartwatch with Quad-core 1.2 GHz Cortex-A7 CPU, 1GB RAM. The device runs Wear OS H-MR2 and is compatible with Bluetooth 4.2. For this study, we recruited eight participants - 4 female and 4 male from age 22 to 47. The participants are encouraged to use their own vehicles and smartphones for this study. There are four different types of vehicles used in this experiment including a Nissan Sentra(sedan), Honda Civic(compact sedan), Ford F-150(pick up truck), Toyota RAV4(SUV). All the vehicles are equipped with in-car Bluetooth. The smartphones involved in the study are Google Pixel 4a, Google Pixel 6, OnePlus 8, Samsung Galaxy S5 and Samsung Galaxy Note5. We asked the participants to put their smartphone at the locations where they are commonly placed on the vehicle.

Real-World and Simulated Driving Scenarios. To fully evaluate the effectiveness of our system, we conduct the experiments with both real-world driving and simulated driving. The real-world driving is used to represent the safe driving where participants are asked to keep their hands on the steering wheel all the time. For safety reasons, only the simulated driving is used to mimic the unsafe driving where participants can take their hands off the steering wheel and conduct five distracted driving behavior discussed before. We conduct the simulated driving under two scenarios. For the first scenario, the participant is asked to conduct different distracted driving behaviors while the car is stopped at the parking lot. For the second scenario, the participant is asked to conduct different distracted driving behaviors in a lab environment including the steering wheel simulator (i.e., Logitech G920 Driving Force Racing Wheel and Floor Pedals) resemble the real driving environment. We acknowledge that the simulated driving is different from real-world driving especially for the lab simulation scenario. Specifically, there are psychological

and physical differences between the real driving on road and the simulated experiments, which could affect participants' behavior. However, it is considered dangerous and possibly illegal to ask a participant to perform any unsafe behavior under real-world driving scenario. To resolve this issue, we will recruit participants for a long-term study to monitor and record their daily driving behavior in the future work.

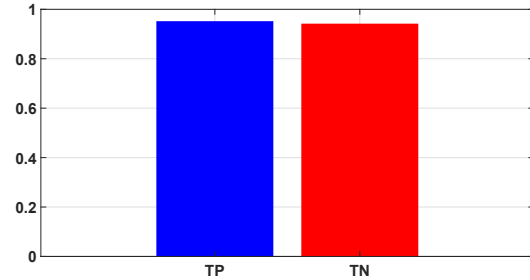


Fig. 3. Overall performance.

Data Collection. There are five different distracted driving behaviors are studied in the experiment including: A) using mobile devices, B) eating/drinking, C) operating on-vehicle system, D) searching onboard item and E) Grooming. They are considered because they are the most common distracted driving behavior found in everyday driving scenario [23]. During the driving period, a camera is used to record the ground truth and all the data collected are labelled manually. We record over 100 minutes of real-world driving data and 75 minutes of simulated driving data. In the real-world driving scenario, we select three different routes including campus route, suburban route and highway route.

Metrics. We use the following metrics to evaluate the performance of our systems. True positive rate (TP) is the proportion of distracted driving behavior that are correctly identified. True negative rate (TN) is the proportion of the non-distracted driving behavior that are correctly not identified as distracted driving behavior. Detection accuracy is the proportion of correctly identified distracted driving behavior.

B. Overall Performance

Fig 3 shows the TP and TN for distracted driving detection under all driving scenarios. We can observe that the rate of our system to successfully detect the distracted driving is over 95%. This shows that our system is highly effective and accurate to detect various distracted driving behaviors. Meanwhile, the TN of our system is over 94% which shows our system could achieve high detection accuracy while maintain low false alert rates.

C. Impact of Number of Bluetooth Devices

Next, under the simulated driving scenario in the stopped car, we study the impact of number of Bluetooth devices on system performance. Specifically, we evaluate the performance of our system using up to four Bluetooth devices. It is worth noticing, our system will always have at least one Bluetooth

device from the vehicle available during the driving period. Driver and passengers can also bring their own devices on the vehicles. As shown in Fig 4, our system can achieve around 90% detection accuracy even there is only one Bluetooth device available and the detection accuracy can be increased to 99% when four Bluetooth devices are being used (One driver phone and two passenger phones). This is because with more Bluetooth compatible devices, the Bluetooth ranging accuracy can be further improved which will lead to better detection accuracy.

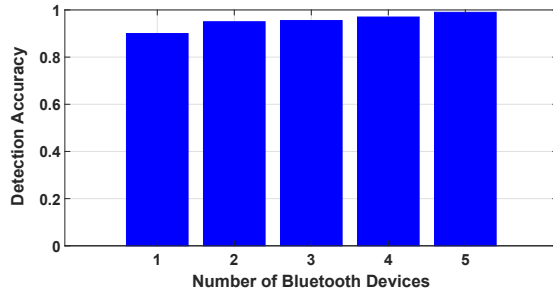


Fig. 4. Detection accuracy under number of Bluetooth devices.

D. Impact of Different Smartphones

As the users will use their own devices during the driving period which could vary in sizes, hardware, and OSs, we then study the performance of our system using different smartphone models. For this study, there are only two Bluetooth devices in the vehicle (car Bluetooth and driver phone) and the smartphone is placed at the cup holder. Fig 5 shows the detection accuracy results under different smartphones. We can observe that all the smartphone models achieve around 95% detection accuracy with no discernable difference between devices. Such observations show that our system is robust and compatible with different models of smartphones.

E. Impact of Different Phone Placement

We then evaluate the performance of our system under different phone placement in the vehicles since users might place their smartphones at different locations within the vehicle. We study four different phone placements including dashboard, pocket, cup holders, and driver door, which represents the typical locations of phone that commonly stored in real-world driving scenarios. Fig. 6 shows the detection accuracy results for different placements. We can observe that, the longer distance of the phone with respect to the steering wheel, the better detection accuracy our system will achieve. As we can see the dashboard placement has the lowest accuracy which is around 88% because it is too close to the steering wheel which provides less distance diversity compare to other placement. One exception is the pocket with accuracy around 90%, although the pocket placement provide enough distance diversity but due to the fact that leg is moving around during the driving period, it reduce the stability of the Bluetooth reading.

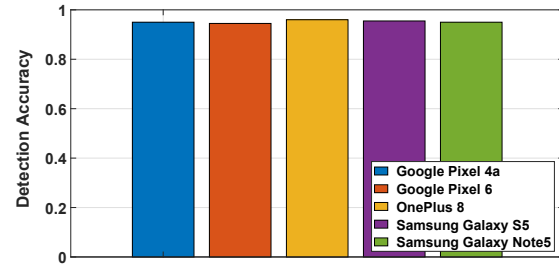


Fig. 5. Detection accuracy for different smartphone models.

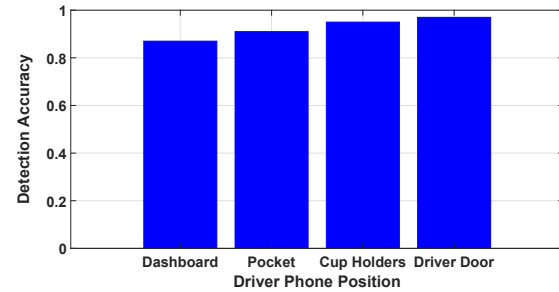


Fig. 6. Detection accuracy for different phone placement.

F. Impact of Different Routes

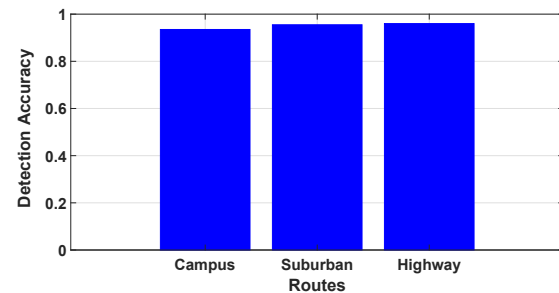


Fig. 7. Detection accuracy for different routes.

Next, we evaluate the performance of our system in different routes including campus, suburban route and highway route to represent different road conditions and driving scenarios in real life. The campus route represents the route with frequent full stops and corner turns; the suburban route represents the route with moderate stops and turns and the highway route represent the route with almost no stop and smooth turn. The detection accuracy results is shown in Fig 7. We can observe that the campus route has the lowest detection accuracy which is around 94% and highway route has the highest detection accuracy which is around 97%. This is because the campus route involves more sharp turns and hand motion which could cause more false alert that can reduce the accuracy. On the other hand, the highway route almost has no stop and much less hand motion involvement which could lead to better detection accuracy. Additionally, drivers usually stay more

alert on the highway compare to the local route which could potentially contribute to the detection accuracy difference.

G. Performance over Different Distracted Driving Behaviors

We then study the performance of our system when driver is conducting 5 distracted driving behaviors discussed in *Data Collection* to have a better understanding over those behaviors. For each of the action we build a separate profile for the participant which is only for this detailed study and not required for our system to work. The confusion matrix for the 5 different actions is shown in Fig 8. As we can see the detection accuracy is over 96% for all distracted driving behaviors while grooming and using mobile devices have the lower detection accuracy compare to others. This is because the time period of grooming action is usually shorter compare to other actions which make it more difficult to detect.

A	0.95	0.02	0	0.02	0.01
B	0.01	0.96	0	0.02	0.01
C	0.01	0	0.97	0.01	0.01
D	0	0.01	0	0.99	0
E	0.02	0.02	0.01	0.01	0.94
	A	B	C	D	E

Fig. 8. Confusion matrix for different distracted driving behaviors.

H. Power Consumption

According to existing work [24], the energy consumption rate for devices utilizing Bluetooth 4.2 is less than 40mW per ms which means the total energy consumption when using our system is amounted to 326.4 μ A per day. Considering the battery capacity of regular smartphones is more than 2500mAh, our system only consumes less than 1% of the total battery capacity even if it is being used all day.

V. CONCLUSIONS

In this work, we propose a wearable-based distracted driving detection system leveraging Bluetooth. By sending the probe signals from multiple Bluetooth compatible devices on the vehicle to the smartwatch worn by the driver, our system can infer the hand position with respect to the steering wheel and recognize the hands off events for distracted driving detection during the driving period. Our system achieves implicit profile construction and update leveraging the time period where the vehicle pull out of the park area without user active cooperation or awareness. Additionally, the proposed system utilizes only Bluetooth sensors to achieve low energy consumption compare to other wearable-based approaches. The experimental evaluation demonstrates that the proposed system can achieve over 95% accuracy in detecting distracted driving behaviors. Results also show that our system can work with different phone models and limited number of Bluetooth compatible devices on the vehicle.

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