Leveraging Wearables for Steering and Driver Tracking

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***Abstract*—Given the increasing popularity of wearable devices, this paper explores the potential to use wearables for steering and driver tracking. Such capability would enable novel classes of mobile safety applications without relying on information or sensors in the vehicle. In particular, we study how wrist-mounted inertial sensors, such as those in smart watches and fitness trackers, can track steering wheel usage and angle. In particular, tracking steering wheel usage and turning angle provide fundamental techniques to improve driving detection, enhance vehicle motion tracking by mobile devices and help identify unsafe driving. The approach relies on motion features that allow distinguishing steering from other confounding hand movements. Once steering wheel usage is detected, it further uses wrist rotation measurements to infer steering wheel turning angles. Our on-road experiments show that the technique is 99% accurate in detecting steering wheel usage and can estimate turning angles with an average error within 3.4 degrees.**

I. Introduction

While the emerging ecosystem of mobile and wearable devices is often viewed as a distraction that can lead to accidents (e.g., [1]–[4]), it also presents opportunities to prevent accidents through safety services. Mobile and wearable safety apps differ from conventional built-in automotive safety systems, which are typically constructed as stovepipe systems focusing on a specific risk and employ dependable systems techniques such as multiple levels of redundancy, quantifiable guarantees on both the timing and paths of state transitions, and precision sensing. There is considerable interest in using mobile devices to deliver softer safety services, however, since they promise low-cost designs that reach a much larger population.

Existing mobile solutions have used inertial sensing on smartphones to detect distracted driver behaviors and monitor driving [5], [6]. In order to apply mobile sensing to driver behavior analysis, the devices also need to recognize when their user is driving and distinguish that from being a passenger. To date this has been addressed through techniques that allow the phone to sense its position inside a vehicle and determine whether it is in the driver area [7]–[9]. Such smartphone-based sensing techniques remain limited in accuracy, however. For example, it is challenging to track very gradual transitions across lanes or to determine that a user is driving when the phone is placed on the passenger side of the vehicle. Moreover, increasingly automated and self-driving vehicles will likely let drivers relinquish driving duties for part of a route. Current smartphone-based sensing techniques cannot determine whether a driver is in charge and has the hands on the wheel.

We therefore ask whether the emerging quantity and diversity of wearable devices can be exploited to achieve more accurate sensing and operation independent of the vehicle. Apart from some early results [10], the use of wearables in this domain has so far remained unexplored. Towards this goal, this paper examines the benefits of wrist-worn inertial data, such as those from smart watches or fitness bands, when combined with phone measurements. Such data is particularly useful for tracking hand movements and can therefore provide information about the driver's vehicle operation—most notably steering wheel usage. To allow more accurate identification of driving, we first develop an inertial detection technique that can detect whether the hand is on the steering wheel based on the hand movements of the driver captured by inertial sensors. We then extend this technique to also track the turning angle of the steering wheel. This information can allow for more precise vehicle motion tracking than gyroscope data and was previously only available through proprietary interfaces to the vehicle CAN bus.

Tracking the usage of the steering wheel can help monitor driving behaviors and identify unsafe driving. For example, the steering wheel turning angles could be used in lane departure warning system to warn a driver when the vehicle is about to drift across the lane. Moreover, unsafe driving behaviors such as swerving, understeer or oversteer could also be detected based on the steering wheel turning angles and other inertial or speed measurements. Just knowing whether a drivers hands are on the steering wheel is also useful context information that mobile apps can use to minimize distractions to drivers.

The contributions of our work are summarized as follows:

- We explore the use of wrist-wearable devices, such as smart watches and wristbands, to track fine-grained driving behaviors including steering wheel usage and angle.
- We design a hand on/off steering wheel usage detection method that relies on hand movements of the driver captured from the wrist-wearable device.
- We propose a steering wheel angle estimation approach by leveraging the wrist rotation caused by the movement of rotating the steering wheel. The

proposed approach takes as input the gyroscope reading of a wrist-wearable device, and the relationship between the wrist and steering wheel rotations, for real time steering wheel angle estimation.

- We demonstrate through experiments in real driving scenarios that it is feasible to track fine-grained driving behaviors using wrist-wearable devices. Our experiments show 99% accuracy in detecting steering wheel usage and estimation of turning angles with an average error of 3.4 degrees, when the hand remains on the steering wheel.

II. Related Work

There have been active research efforts in reinforcing driving safety by utilizing mobile devices used in vehicles [5]–[7], [9], [11]–[15]. Some prior contributions have been made to detecting whether the mobile device user is a driver or passenger [7], [9], [11], [16], which can facilitate many applications aiming to mitigate distracted driving, whereas many works have been done to evaluate or classify driver behaviors by leveraging mobile sensing technologies (including using embedded sensors, cameras and other auxiliary devices (e.g., OBDII) in mobile devices or vehicles) [5]. In addition, there are studies on solving driving safety issues by detecting dangerous steering wheel motions [17], [18].

In particular, Yang et al. [11] introduce an acoustic ranging system to identify the location of a smartphone in the vehicle using its audio infrastructure. Wang et al. [7] utilize embedded sensors in a smartphone and a reference point (e.g., an OBD device) to capture vehicle dynamics, which can be further exploited to determine whether the phone is on the left or right side of the vehicle. However, both works rely on access to extra infrastructures in a vehicle, which may not be widely available and thus reduce the chance of adopting the approaches quickly among a large number of users. Some other work [9], [16] distinguish whether the phone is used by a driver or passenger based on the detection of specific movements, such as entry swing, seat-belt fastening, or pedal press using inertial phone sensors.

In terms of driving behavior detection, apps, such as iOnRoad [12], Augmented Driving [13], and CarSafe [19], provide lane changing assistance and safe following distance based on the vision of driver or outdoor environment captured by cameras in smartphones. Also, Sober-Drive [20] and CarSafe [19] detected drowsy driving in a similar manner.These approaches do vision studies based on the camera of the phone. In contrast, inertial sensor based approaches [5], [6], [14], [15] rely less on specific phone placement and more on motion sensing through phone's embedded inertial sensors. Castignani et.al. [5] propose SenseFleet, a driver profile platform that is able to detect risky driving events independently on a mobile device. Chen et al. [6] develop a vehicle steering detection middleware to detect various vehicle maneuvers, including lane changes, turns, and driving on curvy roads. Johnson et al. [14] and Dai et al. [15] both propose driving behavior monitoring systems to track unsafe events based on embedded inertial sensors in the smartphone. However, these approaches have limited accuracy on detectable unsafe driving events, since they only involve smartphones, which more likely capture vehicles' dynamics instead of drivers' dynamics.

Moreover, [18] introduces several models that get driving behaviors from the steering wheel angle. Schmidt et al. [17] present a mathematical model of the steering wheel angle that contributes to predicting lane change maneuvers. However, these approaches need the steering wheel angle data, which is not readily available in mobile devices. [21] used steering-wheel-mounted kinematic sensors to estimate the steering wheel angle. However, this technique still relies on external sensors that need to be deployed and may cause distraction.

In recent years, wearable devices have been exploited for motion estimation in many research works. Vlasic et al. [22] propose a full body motion capture system using inertial sensors. Raiff et al. [23] use a wristband containing a 9-axis inertial measurement unit to capture changes in the orientation of a persons arm, and develop a machine learning pipeline that processes the orientation data to accurately detect smoking gestures. We foresee that wrist-worn wearable devices, such as smartwatches and activity trackers, are particularly useful for fine-grained tracking driving behaviors, because they capture the dynamics directly from user's hand movements. Different from the above works, we propose a low-infrastructure approach to accurately determine steering wheel turning angles based on both smartwatch and smartphone, which can be used as an input for many driving safety applications.

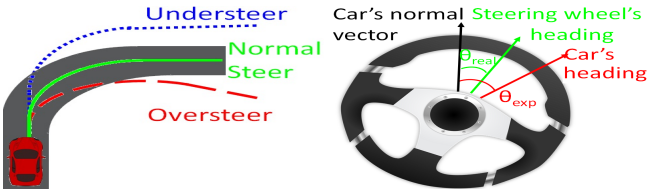
III. Applications and Requirements

The observations that can be gathered from mobile and wearable devices open new research opportunities that would be impossible to develop with existing built-in, stovepipe automotive safety systems. The steering wheel usage is one example - it can be used to analyze drivers' behaviors, but also to inspire additional driver safety applications. Although cars equipped with Electronic Stability Control (ESC) could utilize steering wheel angles to determine a driver's intended direction, steering wheel angle information is not usually accessible from the OBD-II port, and therefore not available for third party applications.

We show that the steering wheel angles can be accurately estimated leveraging a wearable device on the driver's wrist. The *estimated steering wheel angle* (θ_{est}) can further facilitate various safety and driver behavior monitoring applications, which will be discussed in Section III-A. Although the *real steering wheel angle* (θ_{real}) could be measured more accurately through the car's built-in systems, the accuracy of the estimated angle may still be useful for the applications with lower accuracy requirements such as understeer/oversteer detection. In Section III-B, we calculate the required accuracy in estimated steering wheel angle in order to achieve desired error rates.

A. Steering Wheel Tracking Applications Scenarios

Detecting Understeer and Oversteer. One of the critical applications of steering wheel tracking is understeer/oversteer detection. In the simplest terms, oversteer is what occurs when a car steers by more than the amount commanded by the driver. Conversely, understeer is what occurs when a car steers less than the amount commanded by the driver due to traction loss as illustrated in Fig 1a. In addition to estimated steering wheel angle and real steering wheel angle, we define another term, the *Expected steering wheel angle* (θ_{exp}) which



(a) Understeer and oversteer are in blue and red. Green line represents driver's intended steering.

(b) The real steering wheel angle and the expected steering wheel angle from car's heading.

Fig. 1: Car and steering wheel for understeer/oversteer.

(a) No oversteer

(b) Oversteer

Fig. 2: Estimated Steering wheel angle and corresponding True positive, False Positive, False Negative, and True Negative regions are illustrated.

is the steering wheel angle that can be calculated based on the car's movement. When there is no understeer or oversteer, the expected and real steering wheel angles should be ideally equal since the car moves as directed by the steering wheel. However, when an understeering or oversteering incident happens, there will be a difference between the two values. Therefore, understeer/oversteer can be detected when this difference exceeds a threshold value (θ_{th}) during the car's turn.

By combining basic circular motion laws and Ackermann steering geometry [24], the expected steering wheel angle can be calculated from centripetal acceleration and angular velocity of the car with following equation:

$$\theta_{exp} = \frac{1}{k} arctan\Big(\frac{2\omega^2}{(2a + d\omega^2)L}\Big), \tag{1}$$

where a, ω, d, and L represent centripetal acceleration, angular velocity, width, and length of the car, respectively. Lastly, k is the coefficient that maps car's steering wheel angle to wheel angle.

Curve Speed Warning. Generally, vehicles have over five times higher accident rates on curves than that on straight roadways [25]. Transportation authorities thus took actions, such as placing dangerous curve warning, to prevent drivers from moving through a curve at a dangerous speed. However, there are still many sharp roadway curves without any warning signs or advisory speeds posted. Additionally, accident risks may still exist, even with warning signs, since the warning signs may be overlooked.

Thus, one example application type that enhances driver safety are Curve Warning Systems (CWS). These assess threat levels for vehicles approaching curves and provide timely driver feedback. The maximum safe speed of a vehicle for an approaching curve is normally affected by both road conditions (e.g., weather conditions) and vehicle behaviors, such as the type of the vehicles (sedan, truck, etc.) and steering wheel rotations. One possible CWS might use crowd-sourcing to determine the maximum safe speed of a vehicle for each upcoming curve by using historical safe turning data sets of other vehicles passing this curve (i.e., without understeering/oversteering happen). The CWS would select the data sets to match the road conditions and vehicle behaviors of the current vehicle to narrow down suitable observational sets and calculate the optimum speed of the vehicle for the curve. The CWS could warn the driver visually if the speed of the vehicle is larger than the calculated optimum speed.

Other applications. Tracking steering wheel usage can lead to many other applications. For example, by comparing estimated and expected steering wheel angles, not only during the turns, but continuously, a car maintenance system can decide whether or not a car needs alignment if there is a persistent offset between estimated and expected steering wheel angles. Also, the steering wheel angle expectation based on online maps for a specific road can be utilized to detect lane changes by comparing the estimated steering wheel angle. The same system can further be useful to detect impaired driving if abnormally frequent lane changes are detected. Similarly, the system can be used to monitor driving styles and report dangerous driving habits. Another interesting application would be gesture-based input system, the driver could interact with the vehicle by rotate his hand on the steering wheel without actually moving it. Such a gesture-based input system can enable drivers to change the radio volume without moving their hand off the steering wheel. However, these type of applications are beyond the scope of this paper.

B. Accuracy Requirement of Understeer/Oversteer Detection

We believe that the coarse data can be still useful for a wide range of applications. In this section, we thus analyze the steering wheel angle estimation accuracy needed to deliver various minimums on classification performance for slip detection. We calculate the allowed deviation of estimated steering wheel angle from real steering wheel angle for an example oversteer detection application with performance criteria, namely *minimum slip detection angle* ($MSDA$) and *error rate*. (e_r). However, the similar calculations can be carried out for understeer and lane change detection application scenarios.

These two metrics ensure that the system's error rate will always be less than e_r as long as the degree of slipping is greater than $MSDA$. The metric we choose for the error rate is Equal Error Rate which is the error rate of the system when the probability of *false positives*, false oversteer detections, and that of *false negatives*, missed oversteers, are equal. Therefore in order to calculate the error rate, we need to define rate of false oversteer detections and the rate of missed oversteers first.

For the false positives, we need to consider the case where the car does not slip. The real steering wheel angle and the expected steering will be equal and have the value of θ_{real}. The estimated steering wheel angle can be modeled as a normal distribution with mean θ_{real} and σ_{steer} standard deviation as in Fig. 2a. The σ_{steer} is the estimated steering wheel angle requirement that the estimation algorithm needs to achieve the aforementioned guarantees. Any θ_{est} angle that is greater than $\theta_{real} + \theta_{th}$ will result in false positives. In order to calculate the false negatives, we need to consider the case when the car's slipping causes $\theta_{slipping}$ degrees of difference between the real steering wheel angle and the expected steering wheel angle. The estimated the steering wheel angle can still be modeled

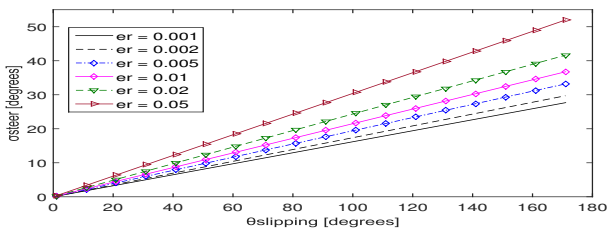


Fig. 3: The required steering wheel accuracy (σ_{steer}) for given error rate (e_r) and slipping angle ($\theta_{slipping}$) is plotted.

		Error Rate (e_r) [%]						
		0.1	0.2	0.5	1	2	5	10
Minimum Slip Detection Angle (MSDA)[^{o}]	1	0.16	0.17	0.19	0.22	024	0.30	0.39
	5	0.81	0.87	0.97	1.07	1.22	1.52	1.95
	10	1.62	1.74	1.94	2.15	2.43	3.04	3.90
	20	3.24	3.47	3.88	4.30	4.87	6.08	7.80

TABLE I: The required steering wheel angle accuracy (σ_{steer}) is given for desired error rates (e_r) and Minimum slip detection angles (MSDA)

with the same normal distribution. The false negatives will occur for the values of the estimated steering wheel angle greater than $\theta_{real} + \theta_{slipping} - \theta_{th}$ as shown in Fig. 2b. From these figures, the σ_{steer} can be calculated for given $\theta_{slipping}$ and e_r can be calculated as follows

$$\sigma_{steer} = \frac{\theta_{slipping}}{2\sqrt{2} * erf^{-}(1 - 2e_r)}, \tag{2}$$

where the $erf()$ is the error function. The σ_{steer} for some e_r and $\theta_{slipping}$ are given in Figure 3. The figure shows that the smaller $\theta_{slipping}$ values require higher accuracy in steering wheel angle estimation system. Therefore, we need to set a minimum slip detection angle in order to define the upper limit of required accuracy. Some example values of required σ_{steer} are presented in Table I for different $MSDA$ and e_r requirements.

IV. System Design

In this section, we first provide an overview of our wearable device based steering and driver tracking system. We then present in detail the proposed hand on/off steering wheel detection and the steering wheel angle estimation methods.

A. System Overview

The basic idea of our system is to use wrist-mounted inertial sensors to capture the hand movements and wrist rotation of the driver for tracking steering wheel usage and angle. As shown in Figure 4, the system takes as input real-time sensor readings from both the wearable device and its paired smartphone including the accelerometer, gyroscope, and magnetometer readings. It then performs coordinate alignment to align the sensors' readings of wearable device and smartphone under the same coordinate system. Coordinate aligment utilizes magnetometer and accelerometer readings in order to find the rotation of devices with respect to earth coordinate frame and then finds an rotation matrix that maps one sensor's readings to the other sensor's coordinate frame. The system then detects whether a user with the wearable device is a driver or a passenger using an existing technique which distinguishes driver's steering motion from other confounding hand movements of passenger and achieves up to 98.9% accuracy [10].

The core elements of our system are the *Hand On/Off Steering Wheel Detection* and *Steering Wheel Angle Estimation.* If a driver is detected, our system then continuously detects when driver's hand is on/off the steering wheel. It could be done by identifying when the drivers hand is moving away from and moving back to steering wheel based on the captured hand movements of the driver. During the periods when driver's hand is on the steering wheel, we further estimate the turning angle of the steering wheel based on the wrist rotation caused by the movement of rotating the steering wheel. The output of our system, for example, driver's hand is on/off steering wheel and the steering wheel rotation angle, could be used as input to build a broad range of driving safety applications, such as curve speed warning, understeer/oversteer estimation, unsafe lane changes, and distracted driving.

B. Hand on/off Steering Wheel Detection

As showed in Figure 4, in order to estimate whether a driver's hand is on or off the steering wheel, we first perform *Hand Movement Detection* to capture all the driver's hand movements except for rotating the steering wheel. Intuitively, for the period when the driver's hand leaves the steering wheel, there must be two movements. One is the *Departure Movement*, which indicates driver's hand moved away from the steering wheel and happens at the beginning of hand off period. The other is the *Returning Movement*, which means driver's hand is moving back to the steering wheel and happens at the end of the hand off period. For each pair of departure movement and returning movement, the driver's hand always moves to opposite linear and rotational directions with respect to the steering wheel. Therefore, after hand movement detection, we perform *Linear Direction Estimation* and *Rotational Direction Estimation* to extract the linear and rotational moving directions of each hand movement. We then combine the linear and rotational direction information to match each pair of departure and returning movements. Thus, the period that between each pair of matched movements are hand off steering wheel period, the rest are hand on steering wheel periods.

Hand Movement Detection. To detect driver's hand movements with respect to the steering wheel, we need to eliminate the effect of car's motion from driver's wrist sensor reading. This could be done by subtracting the car's acceleration and gyroscope readings from the ones of the wearable device after coordinate alignment. We then get the acceleration and angular speed only produced by hand's movement. We further smooth the wearable device's readings to reduce noise by using a low pass filter. We experimentally find that the gyroscope is more reliable for hand movement detection than that of acceleration. We thus examine the peaks (i.e., local maximum) of the magnitude of gyroscope reading to detect the time when hand movements may happen.

After getting peaks of gyroscope magnitude, we perform peak clustering in the time domain. As each movement could be related to multiple continuous peaks in a specific time domain, we could then filter out vibration noise and the motion corresponding to slight hand movements (which are also keeping hand on the steering wheel) by excluding those clusters that contain less numbers of peaks. Therefore, after peak clustering, we can get each hand movement, starting at the first peak in each cluster and ending at the last peak in the same cluster.

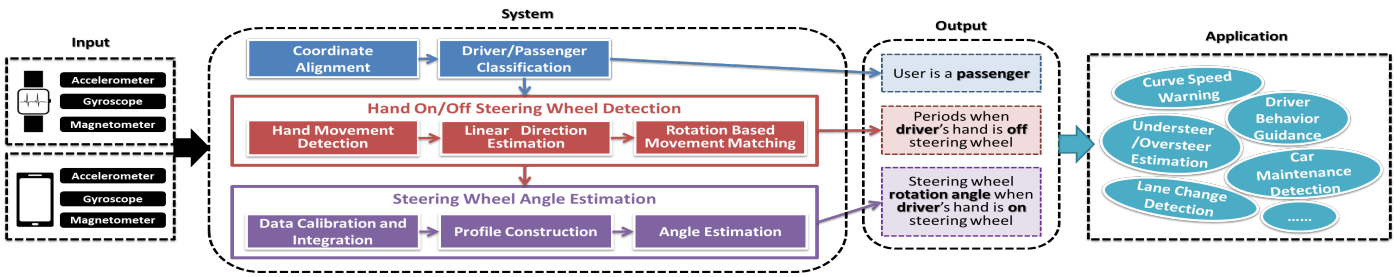


Fig. 4: System overview.

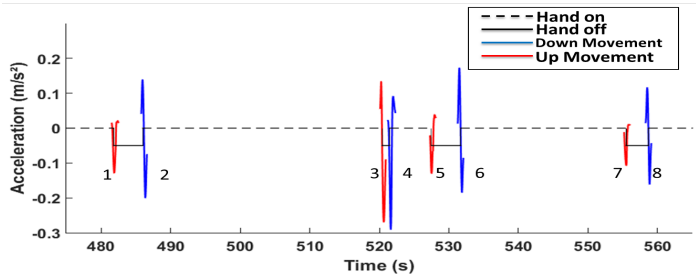


Fig. 5: Linear Direction Estimation

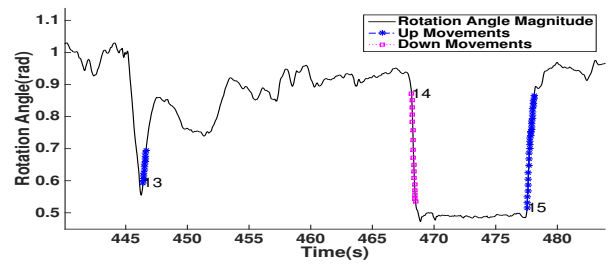


Fig. 6: Rotational based matching

Linear Direction Estimation. During each movement period, estimating the linear moving direction is helpful to characterize and match the movements. For the three axis of the car's coordinate system, the x and y axis are always more noisy. We thus always estimate the linear direction according to z axis, namely the up and down direction.

As the hand always moves from one stationary state to another stationary state for each hand movement, there will be a speed up process and a slow down process. If the hand speeds up towards the up direction (i.e., large acceleration with negative readings) and then slows down, it means the hand is moving up, and vice versa. We thus can exam the sign and the magnitude of the acceleration to identify the moving direction of the hand. Figure 5 & 6 show the acceleration and rotation angle measurements from a wearable sensor placed on the arm. As shown in Figure 5, the black horizontal dash and solid lines show the ground truth when hand is on and off the steering wheel respectively and eight curves show the movements we detected. The acceleration pattern we mentioned above is obvious for the 2nd, 3rd, 4th, 6th, 8th curve, but is indistinct for 1st, 5th and 7th curve. It is because sometimes the effect of gravity could not be perfectly eliminated. Therefore, we add one more rule to estimate the movement direction. That is if the maximum value of the z axis acceleration is less than 0.01, this movement is a up movement (because the maximum value is supposed to be a larger positive value). Therefore, based on the two patterns we find in the z axis acceleration value, we could estimate whether a movement is either a up movement or a down movement.

Rotational Based Movement Matching. The main principle of movement matching is the departure and returning movements must have different moving directions. Thus, we first find all adjacent paired movements with opposite direction and regard all such pairs as potential matching. However, some events such as sudden braking or bumpy road conditions may cause dramatic changes of both the accelerometer and gyroscope values, which may lead to an incorrect movement detection and even an incorrect hand off period detection. As shown in Figure 6, Movement 13 is an incorrect hand movement detection, while 14 and 15 are a pair of departure and returning movements.

To solve this problem, we calculate the rotation angle of the watch respect to the smart phone, and use its magnitude to monitor the angle changes of the watch. Since the driver's hands always have slightly continuous movements when his hands are on the steering wheel, while during the hand off period, his hands are relatively stable, we developed a variance filter to reduce matching errors. This filter simply calculates the variance between two potential matching movements and sets a threshold (0.002 rad in our system) to remove those match with a large variance. In the example in Figure 6, the variance between 13 and 14 is 0.004 rad while the variance between 14 and 15 is 0.0003 rad. We therefore match movement 14 and 15 together. By applying this rotational based movement matching, the system provides more accurate hands on/off steering wheel detection to facilitate steering wheel angle estimation.

C. *Steering Wheel Angle Estimation*

Once steering wheel usage is detected, we further use the wrist rotation of the smart watch to infer the steering wheel turning angles. When the driver rotates the steering wheel, the smart watch also experiences wrist rotation as it rotates together with the steering wheel. The steering wheel angle thus could be inferred from the wrist rotation of the smart watch. In particular, we use the gyroscope readings of smart watch to measure the wrist rotation for steering wheel angle estimation.

In the coordinate alignment step of the system, we align both the car's and the smart watch's coordinate systems with the steering wheel's. By aligning these coordinate systems, we are able to project the gyroscope readings of both the car and the smart watch to the plane of the steering wheel. We then perform *Data Calibration and Integration* to remove the effect of car's motion (i.e., car's rotation) and integrate the gyroscope readings (i.e., angular velocity) to rotation angle. After this

Fig. 7: Holding position and the projected position of smart watch on steering wheel.

step, we obtain the wrist rotation of smart watch with respect to the steering wheel's rotation. Such wrist rotation is then used in *Angle Estimation* to infer the steering wheel angle based on the constructed driver rotation profile in *Profile Construction*. In this study profile construction is studied for a single driver and a more generic driver rotation profile construction is left as a future work.

Data Calibration and Integration. When a car makes a turn, the gyroscope readings (i.e., angular velocity) of the smart watch are a combination of the angular velocities of the steering wheel rotation and the car. As the car's angular velocity can be measured by the phone inside the car, we simply subtract the car's angular velocity from the angular velocity of the smart watch after coordinate alignment. We then obtain the angular velocity of the smart watch which solely corresponds to the steering wheel rotation. Such angular velocity is then integrated to wrist rotation angle with respect to the steering wheel. We define such wrist rotation as θ_{wrist}.

Profile Construction. Ideally, we expect the wrist rotation θ_{wrist} equal to the steering wheel angle θ_{real} when making turns. However, we experimentally find that the wrist rotation of the smart watch is usually less than that of the steering wheel. This is because the driver bends his wrist in different ways when holding the steering wheel under different turning angles. As shown in Figure 7, before making a turn, the wrist has a large angle to the steering wheel plane. The projected location of the smart watch on the steering wheel is thus close to the holding position. After a 90 degree turn, the wrist angle to the steering wheel plane becomes smaller, which leads to the projected location farther away from the holding position. The rotation of the smart watch is thus smaller than that of the steering wheel. Moreover, the attitude change of the watch is mainly due to the wrist rotation instead of the translation movement following the trajectory of the steering wheel movements. Thus, the smart watch mainly rotates side to side on the wrist. These factors makes the smart watch rotation significantly less than that of the steering wheel rotation angle.

To address the aforementioned issue, we use a supervised learning method to create a driver rotation profile. In particular, we collect training data offline to create a mapping (i.e., a function $f(x)$ such that $\theta_{real} = f(\theta_{wrsit})$) between the rotations of the smart watch and the steering wheel turning angles. This is based on the observation that people usually consistently bend their wrists when turning. The steering wheel turning angles thus can be inferred based on the wrist rotation

Fig. 8: Position of sensors and smartphone.

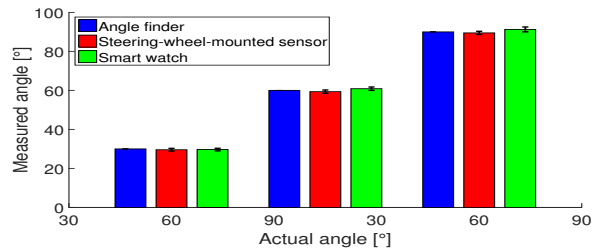
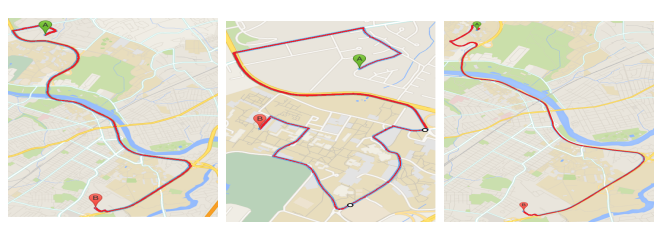


Fig. 9: Measurements from angle finder, smart watch, and steering-wheel-mounted sensor

of smart watch (i.e.,θ_{wrist}) and the created angle mapping (i.e., $f(x)$). To create the driver rotation profile, we use a gyroscope sensor aligned with the steering wheel to measure the real steering wheel angles, and then use liner regression to fit the smart watch rotation θ_{wrist} to the measured steering wheel angle. We experience with different models, such as linear, quadratic and cubic fits, and find that the linear fit is simple yet effective.

To construct the profile, we could also use a semi-supervised approach. It uses the smart phone inside the car to monitor the centripetal acceleration and angular velocity of the car when making turns to calculate the angle of the steering wheel. When there is no understeer/oversteer, the steering wheel angle could be calculated based on the circular motion laws and Ackermann steering geometry [24], as shown in equation 1. We could then build the profile automatically based on the real-time measurements of the θ_{wrist} and the calculated steering wheel angles. After the profile is constructed, we can then infer the steering wheel angle based on wrist rotation of the watch θ_{wrist} for building higher level safety applications, such as understeer/oversteer detection and curve speed warning.

Angle Estimation. By plugging in the real-time θ_{wrist} to the mapping profile $f(x)$, we could infer the real-time steering wheel angle as $\theta_{est} = f(\theta_{wrist})$.



(a) Highway (b) Local road (c) More movements

Fig. 10: Maps of commute routes.

V. Performance Evaluation

A. Experiment Setup

To evaluate our approach, We conduct experiments with an Invensense MPU-9150 9-axis motion sensor, which is a prototyping alternative to a wearable device. The motion sensor contains 3-axis accelerometers, gyroscopes, and magnetometers. In our experiments, the participants are asked to attach the motion sensor to his/her left wrist, where people usually wear watches. The motion sensor is paired with participant's android smartphone via Bluetooth. The smartphone is placed in the middle cup holder with its coordinate system aligned with that of the car. We align another motion sensor with the steering wheel to record the ground truth of the steering wheel rotation angles when making turns. In contrast to other steering-wheel-mounted sensor based approaches our work is a low-cost and unobtrusive design that can reach a much larger population and focuses on finding the steering wheel angle without requiring any additional sensors. However, obtaining the ground truth is very hard with angle finders in a dynamic while the vehicle is being used. As a consequence, we used steering-wheel-mounted sensors to collect the ground truth. Our experiments with static steering wheel showed that the error in steering-wheel-mounted-sensors is negligibly small (less than 1°) and can be usable as ground truth. Figure 9 shows mean and standard deviations in angle measurements from the angle finder, the steering-wheel-mounted sensor, and the smartwatch. All the other experiments are performed while the car is being driven. Additionally, a GoPro camera is mounted over the driver's shoulder to record the ground truth of the driver's hand movements while driving.

The positions of these devices are shown in Figure 8. The sampling rates of motion sensors and smartphones are set to 50Hz, which is supported by most off-the-shelf wearable and mobile devices, such as the smart watches and fitness trackers. The sensing data of the motion sensor is transmitted to and stored at smartphone via Bluetooth by an app. We have two drivers preform data collection with one driving Honda Civic and using Nexus 5 smart phone and the other driving Toyota Camry and using Nexus 6 smart phone.

We conduct experiments by driving on three routes with different road conditions, as shown in Figure 10. The first two routes, namely *Highway Commute* and *Local Road Commute*, cover the highway and local road commutes (i.e., Figure 10 (a) and (b)), respectively. These two routes cover a wide range of steering wheel angles as highways usually involve smooth curves resulting in small steering wheel rotation angles, and local roads often have sharp turns that cause large steering wheel rotation angles. We collect data for 20 trips over one month on these two routes and the driver is asked to drive naturally. Additionally, in order to evaluate our hands on/off the steering wheel detection algorithm, we intentionally perform more frequent hand on/off movements during real driving on a highway as shown in Fig. 10 (c) .

B. Hand On/Off Steering Wheel Detection Evaluation

We first evaluate how accurately we can detect the driver's hand is on or off the steering. We thus define the positive cases as the driver's hand is on the steering wheel and the negative cases as the driver's hand is off the steering wheel. We measure the duration of hands on/off the steering wheel in terms of number of seconds. Therefore, each positive/negative instance corresponds to the driver's hand is on/off the steering wheel for one second. The one second's resolution is good enough to tolerate the error when we labeling the ground truth manually by checking the video of each commute trip.

We use the true positive rate and true negative rate to measure the overall performance of the hands off/on steering wheel detection. The true positive rate represents the proportion of the period the hand on the steering wheel could be correctly determined, while the true negative rate represents the proportion of the period the hand off steering wheel could be correctly identified. In other words, the true positive rate reflects how accurately our method could activate the steering wheel angle estimation, whereas the true negative rate shows how accurately the method could trigger unsafe driving behavior notification, for example warning driver when his hand is off the steering wheel.

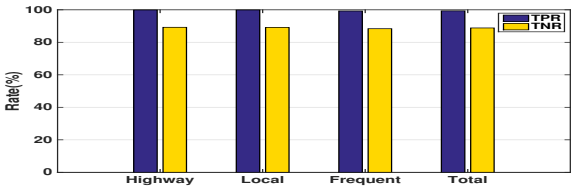
Overall, our hand on/off steering wheel detection achieves a 99.9% true positive rate and a 89.2% true negative rate for the normal commute data set, and a 99.3% true positive rate and an 88.4% true negative rate for the frequent hand movement commute data set. We also evaluate our system in two different commute types: highway and local road. Figure 11 (a) compares the performance of our method on three routes. We observe that different routes have similar performance, which demonstrates our method is robust to different road conditions and different frequencies of hand on/off the steering wheel events. By combining the results from these three routes, our method achieves a 99.4% accuracy on detecting hand on steering wheel periods and an 88.8% accuracy on detecting hand off steering wheel periods.

We next evaluate how accurately our method can detect when the hand is off the steering wheel for different types of hand movements. In the experiments, we tested three different typical hands-off events of drivers, namely *hand on leg*, *hand on the armrest* and *adjusting sun visor*. Figure 11 (b) compares the true negative rates and false negative rates for these three hands-off events. We observe that for both hand on leg and hand on armrest events, the true negative rate remains above 91.5% and false negative rate is less than 8.5%. However, for reaching for the sun visor event, the performance decreases to as low as 81.5%. This is mainly because reaching the sun visor has a smaller moving duration and continuous moving process than that of other two events. Thus, it is relative harder to match the hand movements to the departure movement and returning movement.

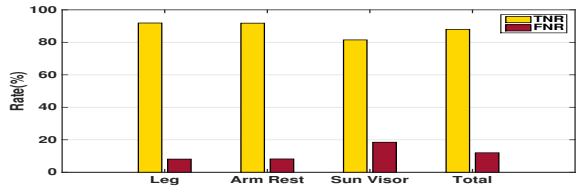
C. Steering Wheel Angle Estimation Evaluation

For the steering wheel angle estimation, we collect 109 turns ranging from 120 degrees right turn to 90 degrees left turn in both the highway commute and the local road commute. The rotation of the steering wheel for these turns is up to 134 degrees. The distribution of the steering wheel rotation for the collected turns is shown in Figure 12. In particular, there are 25 turns with steering wheel rotation less than 30 degrees, 43 turns with steering wheel rotation in between 30 to 60 degrees, and 41 turns with steering wheel rotation larger than 60 degrees.

We use two types of errors, *true error* and *absolute error*, to evaluate the performance our steering wheel angle estimation. The *true error* is defined as the real steering



(a) True positive rates and True negative rates of different data sets.



(b) True negative rates of different kinds of movements.

Fig. 11: Hand on/off detection performance.

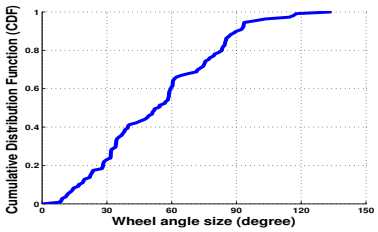


Fig. 12: The distribution of the steering wheel rotation for all the turns.

	[0,30]	(30,60)	> 60	All turns
Mean	0.000063	-0.00012	0.00032	0.000046
Std.	2.21	3.82	6.12	4.93

TABLE II: The mean and standard deviation (in degree) of the true error for the turns with different steering wheel angles.

wheel rotation minus the estimated steering wheel angle (i.e., $\theta_{real} - \theta_{est}$), whereas the *absolute error* is the magnitude of the difference between the true rotation and the estimated angle (i.e., $||\theta_{real} - \theta_{est}||$).

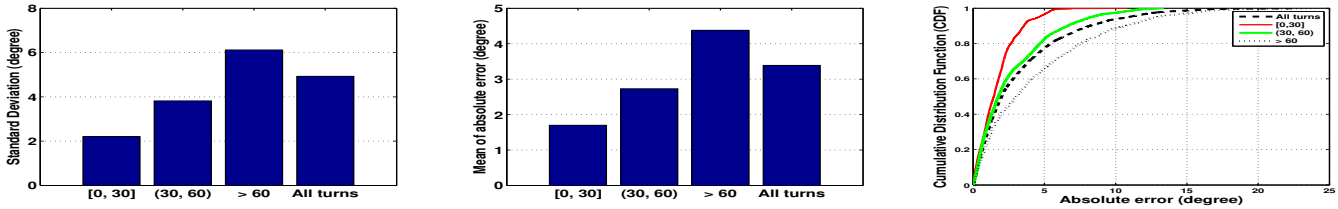
We first evaluate how the estimated steering wheel angle could detect the slipping of understeer/oversteer. Table II presents the mean and standard deviation of the true error under the turns with different rotation ranges of the steering wheel. We observe that the mean of the true error is about zero for all the turns and the turns under different steering wheel rotation ranges. We find the standard deviation of the true error increases when increasing the steering wheel rotation ranges. This is because that with larger rotations on steering wheel, the wrist movement experiences larger variation as well. As we rely on the angle mapping profile $f(x)$ to infer the steering wheel angle, the larger wrist movement variation consequently produces larger variation of the angle estimation.

In particular, Figure 13 (a) compares the standard deviation of the true error for the turns with different steering wheel rotation ranges. We next compare the standard deviation obtained in our experiments with the ones presented in Table I to evaluate the effectiveness of understeer/oversteer detection. We find that the standard deviation for the turns with steering wheel rotation less than 30 degrees is 2.21 degree which results in approximately 99% accuracy when detecting 10 degrees slipping or about 90% accuracy in detecting 5 degrees slipping. Whereas for the turns with steering wheel rotation in between 30 to 60 degrees, the standard deviation is 3.82 which corresponds to about 99.5% accuracy when detecting 20 degree slipping or more than 90% accuracy in detecting 10 degree slipping. The standard deviation for the turns with wheel rotation larger than 60 degree is 6.12 degree which leads to about 95% accuracy when detecting 20 degree slipping. Note that it's more likely that larger rotation of the steering wheel will cause larger angle of slipping. Even if the standard deviation increases when increasing the size of the steering wheel angle, it could still produce high accuracy, 95% to 99% for example, in detecting increased size of slipping angle. We next investigate the absolute error, which describes the magnitude of difference between the true steering wheel angle and the estimated angle. Figure 13 (b) depicts the mean absolute error under the turns with different rotation ranges of steering wheel. Overall, we observe that the mean error is less than 3.4 degrees for all the turns. Moreover, the turns with larger steering wheel rotation have relative larger mean error. Specifically, the mean error for the turns with less than 30 degree steering wheel rotation is 1.7 degrees, whereas it is 2.73 and 4.38 degrees for the turns with rotation in between 30 to 60 degrees and rotation larger than 60 degrees, respectively.

Figure 13 (c) shows the cumulative distribution function of absolute error under the turns with different rotation ranges. Similarly, we observe the curve shifts to right when the rotation of steering wheel becomes larger indicating larger rotation of steering wheel has relative larger error. The median error increases from 1.45 to 1.76 and to 3.04 when the turns with the steering wheel rotation increases from the range of $[0, 30]$ to $(30, 60)$ and to larger than 60 degrees. And the 80% percentile error for the case of $[0, 30]$, $(30, 60)$ and larger than 60 is 2.66, 4.7 and 7.55 degrees respectively. We also observe a large error (e.g., 10 degrees) at the tail of the CDF curve. This is because the driver occasionally bends his/her arm very differently for the same size of steering wheel angle. However, the percentage of such large errors is very small for the turns with less than 60 degrees rotation of steering wheel. For example, it is less than 3% for the case of $(30, 60)$ and less than 5% for all the turns. And the large error becomes less significant for the turns with rotation of steering wheel larger than 60 degrees. It still, however, leaves us room to further improve the angle estimation method for example by combining the accelerometer and gyroscope readings [26]. Overall, the above results show that our steering wheel angle estimation method is effective with a mean error less than 3.4 degrees.

VI. Discussion and Conclusion

In this work, we exploit the opportunity of using wristworn wearable devices to enable activity recognition of unsafe driving. In particular, we develop the fundamental techniques in hand on/off steering wheel detection and steering wheel angle estimation to provide more detailed information in tracking of driving behaviors. We examine whether our proposed vehicle-independent techniques leveraging wearables could achieve sufficient accuracy for building driving safety applications. Through various real-driving scenarios, we show that our approach can achieve hand on steering wheel detection with a true positive rate around 99% and provide warning of unsafe driving when a driver's hand is off the steering wheel with a



(a) The comparison of the standard deviation of the true error for the turns with different ranges of steering wheel angle.

(b) The comparison of the mean absolute error for the turns with different ranges of steering wheel angle.

(c) The cumulative distribution function of absolute error for the turns with different ranges of steering wheel angle.

Fig. 13: Steering wheel angle estimation performance.

true negative rate above 80%. Additionally, our system can achieve accurate steering angle estimation with errors less than 3.4 degrees to facilitate applications such as curve speed warning and understeer/oversteer detection.

Open challenges remain towards realizing automatic steering and driver tracking using sensing techniques independent of vehicles. A limitation of our approach is its statistical nature for safety applications. E.g., detection accuracy decreases if the driver steers only with the watch-less hand. However, we still envision that there exist a range of human behavior modification and attention direction uses for which statistical approaches are useful. Furthermore, our algorithms only need to be activated during driving. For most people, this only occupies a small portion of their day. Thus, the energy consumption incurred by our system should not pose any significant burden to the wearables.

Another potential shortcoming is that we only construct and test the profile of wrist rotation with respect to the steering wheel angle for one driver. We expect such profile is relative consistent for different drivers as the wrist movements are highly constrained by the rotation trajectory of the steering wheel. Still, re-training or fine-tuning the profile may be required for different drivers. Such training efforts, however, could be mitigated by using the semi-supervised learning based method proposed in profile construction step. Furthermore, different drivers may have different styles of wearing the device. For example, the panel of the smartwatch could face down for one driver but face up for another. As the postures/attitudes of the wearable device could be detected by the motion sensors, different postures thus could be calibrated to the one matches the construed profile based on the detected posture.

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