SafeWatch: A Wearable Hand Motion Tracking System for Improving Driving Safety

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ABSTRACT

Driving with distraction or losing alertness increases the risk of the traffic accident. The emerging Internet of Things (IoT) systems for smart driving hold the promise of significantly reducing road accidents. In particular, detecting the unsafe hand motions and warning the driver using smart sensors can improve the driver's self-alertness and the driving skill. However, due to the impact from the vehicle's movement and the significant variation across different driving environments, detecting the position of the driver's hand is challenging. This paper presents SafeWatch – a system that employs commodity smartwatches and smartphones to detect the driver's unsafe behaviors in a real-time manner. SafeWatch infers driver's hand motions based on several important features such as the posture of the driver's forearm and the vibration of the smartwatch. SafeWatch employs a novel adaptive training algorithm which keeps updating the training dataset at runtime based on inferred hand positions in certain driving conditions. The evaluation with 75 real driving trips from 6 subjects shows that SafeWatch achieves over 97.0% recall and precision rates in detecting of the unsafe hand positions.

CCS CONCEPTS

•Human-centered computing →Ubiquitous and mobile computing;

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1 INTRODUCTION

Recent studies revealed that the distractions and the secondary tasks occurring inside the vehicle increase the risk of a road accident by 2 to 10 times [19]. Examples of secondary tasks include using a mobile phone, adjusting air conditioners, operating the on-vehicle entertainments, eating and drinking, etc [8] [15]. Relaxing due to the boredom may also lead to unsafe driving behavior, e.g., one hand unconsciously moved away from the steering wheel. When the drivers are distracted or losing alertness, their braking response time is significantly longer than usual, and they could fail to maintain the control of the vehicle [22]. It is shown that similar to aggressive driving and risky driving, lost concentration and minor loss of control are among the top conditions related to traffic accidents [11].

It is recommended by the *American Automobile Association* (AAA), a driver should hold the steering wheel firmly with both hands at the 9 o'clock and 3 o'clock positions [2]. However, it is difficult for a driver to maintain self-awareness of their hand positions due to boredom or drowsiness of a relatively long trip [34] [33]. Stimulation like music may improve the alertness of the driver while sometimes causing distraction and increasing their mental efforts [35]. Research shows that a system that accurately detects the incoming danger and warns the driver can not only invoke driver's alertness but also enable them to self-improve their driving skills [4]. Recently, the emerging Internet of Things (IoT) systems for smart driving provide a promising solution. Several methods have been developed to detect the driver's dangerous actions [21] [20] [23] [24] [25]. However, these designs require additional devices such as cameras, PPG sensors or pressure sensors, presenting the barrier to wide adoption. More recently, several systems are developed to track the user's hand movement with smartwatches [38][30]. However, they often yield unreliable performance while driving due to the impact of the vehicle's movement. Some studies show that the smartwatches can be used to detect several important driving behaviors like the angle of the steering wheel [27] [18]. However, the performances of these systems are not effective in some cases, especially when the hands rest at positions other than the steering wheel.

Several major challenges must be addressed in the design of high-performance driving monitoring systems based on wearable devices. The motion sensor samples from a smartwatch in a moving vehicle not only contain the hand's movement, but also include impacts from the vehicle's acceleration, turning, and *Noise, Vibration, and Harshness* (NVH) from the engine and the road condition. Due to the significant variation across different devices, drivers, and vehicles, it is difficult to design a robust classification algorithm to detect the hand's position based on motion features. Moreover, the driver may switch postures during a driving trip, resulting in different patterns of motion data.

To address these challenges, we introduce SafeWatch – a system based on wearables and smartphones that can accurately detect the driver'fis hand motions and identify unsafe driving behaviors. SafeWatch samples and processes the data captured by the built-in motion sensors on the smartwatch worn by the driver and the smartphone in the vehicle. It detects whether a hand is holding the steering wheel based on several select features from the motion data, such as posture of the driver's forearm, vibration of the vehicle's body, and the vehicle's turning. SafeWatch employs a novel training algorithm to deal with the significant variation of motion features across devices, drivers, vehicles, roads, and different driving trips. The key idea is based on the observation that the driver's hand must be on the steering wheel to perform a turning, providing ground truth feedback around the moment of turning for training. The performance of SaftWatch is evaluated by 75 real driving trips by 6 subjects. Our results show that, the accuracy of SafeWatch is over 97.0% for both recall and precision in detecting hand positions when the condition lasts more than 6.0s, and over 97.1% recall and over 91.0% precision in detecting the unsafe hand movements when it lasts more than 2.5s. SafeWatch can be integrated with other driving systems to trigger alerts or log unsafe driving behavior for driver training.

2 RELATED WORK

The dangerous action by the driver is mainly caused by drowsiness and distraction [17]. To keep the driver concentrating on the driving, the effective methods include alerting the driver for the incoming danger [4] or giving feedback for the driver's level of drowsiness [1]. These methods require a way to monitor the driver's mental or physical status. The driver's behavior can be recorded by a camera. However, the video-recording raises the privacy concerns. Another approach is to leverage various sensors including motion sensors, barometers, and GPS on the smartphone to monitor the driving style (e.g. risky or aggressive), track the vehicle, and learn the road condition [16] [10] [14] . However, this approach only analyzes the vehicle's movement, and it cannot acquire knowledge about the driver's behavior inside the vehicle. Several efforts attempt to monitor the drivers' drowsiness with proprietary biomedical sensors (e.g. heart rate sensors) [26][7] . However, these sensors are not readily available on off-the-shelf mobile devices.

In recent years, several approaches are proposed to detect the driver's hand position. For example, using the sensors around the steering wheel, the driver will be alerted when his or her hand is not holding the steering wheel due to drowsiness or distraction [21] [20] . Another viable method is to detect the grip strength of the hands with pressure sensors on gloves [23] . However, these methods require additional equipments and raise the burden of usage.

Hand posture recognition using motion sensors on wearables or smartphones has been studied extensively. For instance, the user's finger-writing [37] and the hand gesture [38][30] can be classified using motion features. A common limitation of these methods is that they assume the movement of the user's arm or hand is the only cause of the smartwatch's movement. However, in our case, the vehicle's movement continuously impacts the motion data captured by any device inside the vehicle, and thus those methods cannot be applied here. If the hand is always on the steering wheel, the turning operation can be traced by the smartwatch, including the starting and ending position [27] . A recent study shows that, by detecting the direction of the hand's movement, when the hand leaves from or returns to the steering wheel can be inferred [25]. However, these methods require a precise alignment between the coordinate systems among multiple devices based on magnetometer and compass. Those sensors are often highly inaccurate or unavailable on some devices. Moreover, the direction of the hand's movement only provides partial information about the hand's position. For example, if the driver is handling a complex task like eating, drinking or grabbing an item, the hand's movement will contain a series of different directions, resulting in difficulty to infer when the hand returns to the steering wheel.

Another study of ours shows that the secondary task while driving can be classified by the angle of the driver's forearm rotation [32]. Although this method is effective to detect the driver's behavior, it still needs to know when the hand is on the steering wheel, because the classification is based on the assumption that the hand's movement always starts there.

3 REQUIREMENTS AND CHALLENGES

SafeWatch is designed to help drivers keep concentrated on driving. Specifically, it detects whether the driver holds the steering wheel with both hands, and reports the dangerous actions, e.g. one hand is away from the steering wheel or keeping moving.

SafeWatch needs to meet the following requirements: 1) As it operates in parallel with driving, it must be unobtrusive to use. It cannot interfere with the driver's activity or require any manual input by the drivers at runtime. (2) To ensure wide adoption in practice, the training process of system should be intuitive and require the minimum amount of efforts/time. (3) It needs to detect the positions of hands relative to the steering wheel in a robust way, i.e., across different drivers, vehicles, and smartwatches.

To meet these requirements, three challenges need to be addressed. First, SafeWatch must be able to detect hand motions using accelerometer and gyroscope readings in the presence of significant interference from the movement of the vehicle. For example, the gyroscope on the smartwatch produces highly similar motion features when the vehicle is turning left or the driver is rotating the arm towards left. As a result, the driver hand motion may be falsely classified due to the impact of vehicle movement.

Second, it is challenging to design the training process due to several reasons. First, in order to detect fine-grained hand motions, a training process is necessary for each combination of driver and vehicle. However, the ground truth is difficult to collect without

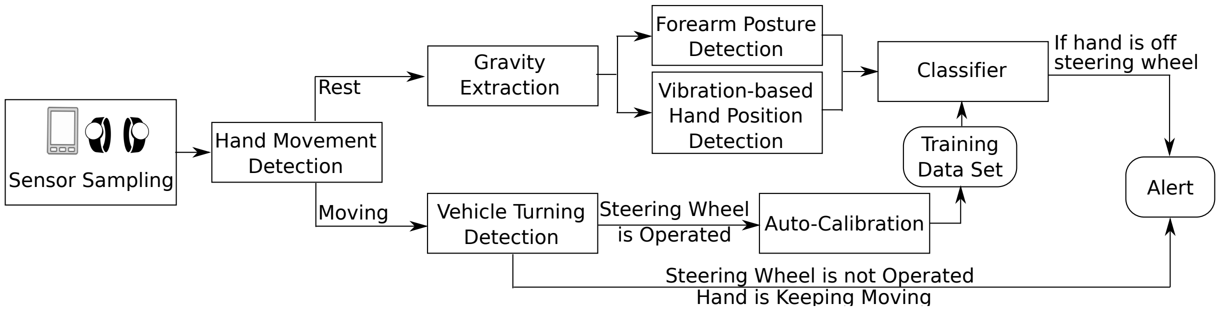

Figure 1: The overview of the system.

user's manual input or video-recording equipments. Moreover, traditional machine learning algorithms require the training set to contain data from both positive and negative classes. That is, SafeWatch should record the motion data not only when the driver's hands are holding the steering wheel, but also when the driver's hands are away from the steering wheel.Such a process is not feasible as it poses potential dangers for drivers. Furthermore, the driver may handle various secondary tasks during driving. Thus the distribution of motion data is highly unpredictable when a hand is away from the steering wheel, presenting challenges for training an accurate classifier. .

Third, the motion data captured by the smartwatch is highly dependent on how it is worn. A typical issue is that the position of the smartwatch on the user's wrist might change due to the hand/arm movement. Moreover, the driver's posture also can change during one driving trip. SafeWatch must adapt itself to such dynamics in order to maintain the accuracy of detection.

4 SYSTEM DESIGN

4.1 System Overview

SafeWatch is a wearable sensing system that can accurately track distracted driver hand gestures. Specifically, it detects if the driver's hands are on/off the steering wheel, which is an enabling primitive for various applications of smart driving and has important implications for improving driving safety. To this end, SafeWatch senses the motion of the vehicle and the driver's hands using a smartphone placed in the vehicle, along with the smartwatch(s) worn on the driver's left and right wrist, respectively. A detector running on the smartphone collects sensing data from different devices and accurately classifies driver hand gestures despite the strong interference introduced by the vehicle's acceleration and turning, as well as noise, vibration, and harshness from engine and road conditions.

Fig. 1 illustrates the architecture of SafeWatch's sensing pipeline. SafeWatch continuously samples and processes the built-in accelerometers and gyroscopes of smartwatches and smartphone. Samples collected from different devices are fused at a hand movement detector, which first mitigates interference introduced by the move of the vehicle, and then detects hand movement based on the processed motion signals. When the hand is moving, SafeWatch detects driver distraction by inferring whether the gesture is a steering wheel manipulation or a behavior related to secondary tasks such as drinking/eating, tuning radio, etc. When the hand is still, SafeWatch classifies hand postures based on two features, including the posture of the driver's forearm learned from the gravity direction of smartwatch, and the vibration sensed on the driver's wrist, which manifests distinct magnitudes when the hand is on/off the steering wheel. In practice, the above features may exhibit different characteristics depending on various factors including the user's driving habits, the posture of the smartwatch, as well as the model of engine that may affect the vibration magnitude of the car body. To maintain robust detection accuracy across different environments, SafeWatch employs an auto-calibrator that leverages sensing data collected while driving to train the hand posture classifier at run-time. In the following, we will describe the design of SafeWatch components in details.

4.2 Sensor Sampling

In SafeWatch, the smartphone placed in the vehicle is employed to monitor the vehicle's movement, while the smartwatches on the driver's wrists track the motion and posture of the driver's hands. In the discussion hereafter, we assume the driver wears a watch on each hand. When the driver wears only one watch, SafeWatch tracks the motion of that hand only. To collect motion data, SafeWatch continuously samples the built-in accelerometers and gyroscopes on the smartphones and the smartwatches. The sampling rate is set to 50Hz. Each sample contains an acceleration vector $\overrightarrow{a}$ and a rotation vector $\overrightarrow{w}$. A sliding window containing 1 second of data is built for every 0.5 seconds. The window size is determined based on two observations. First, it is not necessary to trigger an alert when the driver's hand is only away from the steering wheel less than $1.0s$, because the unsafe actions last more than $2.5s$ as defined by the *American Society of Safety Engineers* (ASSE) [5]. Second, if we wish to trigger the alert when the hand is away from the steering wheel for a relatively long time, e.g. $5.0s$, we wish to analyze the motion data from a considerable amount of previous windows. Thus, we select the length of the window as $1.0s$ for each $0.5s$, in order to capture the detailed motion of driver's hand while minimizing the computing overhead.

4.3 Hand Movement Detection

The goal of hand movement detection is to determine whether the driver's hand is moving. Although the variance of $\overrightarrow{a}$ is effective to detect whether a device is moving at a constant speed or at rest,

Figure 2: The 3-axis coordinate system for the accelerometers and gyroscopes on the smartwatches. The most important fact is, the X-axis is always parallel to the arm, and its direction for the left and right arm is opposite to each other.

it cannot be used for detecting whether a device is moving in a driving environment, where $\vec{a}$ is interfered by the movement of the vehicle. SafeWatch addresses this challenge by comparing $\vec{a}$ from the smartwatch and $\vec{a}$ from the smartphone. Since the coordinates of the smartphone and the smartwatches are not aligned, we cannot directly compare the direction of $\vec{a}$ from those devices. However, an important observation is that $|\vec{a}|$ from those devices should be similar if no relative movement exists between them. Based on this observation, SafeWatch determines if the driver's hand is moving by comparing $|\vec{a}|$ from each devices, and examining the following inequality,

$$\frac{\sum_{i=1}^{l} ||\overrightarrow{a_{i,watch}}| - |\overrightarrow{a_{i,phone}}||}{l} \leq \epsilon \tag{1}$$

where l is the length of the window. When the inequality is satisfied, SafeWatch claims that there is a relative movement between the driver's hand and the vehicle. The performance of the detector given in Eq. 1 depends on the choice of ϵ. Specifically, a small ϵ may degrade the classifier's robustness in the presence of noise motion signals, resulting in an increased false alarm rate. If ϵ is too large, SafeWatch may fail to recognize the movement of the hand, reducing the detection rate. We optimize the performance of the detector shown in Eq. 1 by choosing ϵ based on empirical measurements. Fig. 3 illustrates detection accuracy for different values of ϵ. According to our experiment, $\epsilon = 1.0 m/s^2$ can be common settings for most cases, considering the native offset of the sensors across various devices.

According to a study by ASSE, such distracted movements usually last for longer than $2.5s$ [5]. SafeWatch checks the hand movement in L consecutive sample windows and whether these windows contains operation of the steering wheel. If the steering wheel is detected as not operated by the method introduced in Section 4.8, but the hand keeps moving, an unsafe action will be detected. The performance of the detection can be adjusted by the different choice of L. The hand movement for a short time can be detected as unsafe when L is small. If L is large, SafeWatch will only detect the unsafe action when the hand movement lasts for a long time. In our design, SafeWatch provides an open interface for choosing L. We recommend this value to be chosen by the professionals of safety engineering.

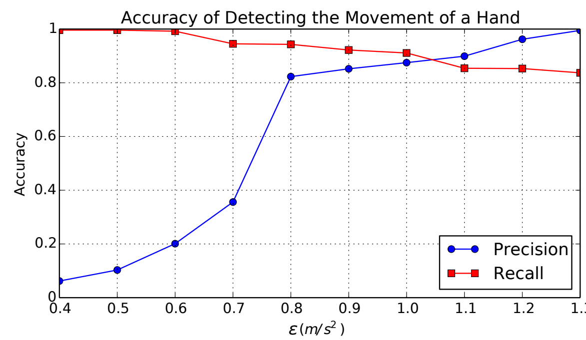

Figure 3: Accuracy of detecting the movement of a hand. The parameter ϵ is selected between 0.4 to 1.3.

4.4 Gravity Extraction

The goal of the gravity extraction module is to learn the attitudes of a device. Moreover, and separates the real acceleration of the device from the effect of the gravity. Since the measurement data $\vec{a}$ from the accelerometer is always interfered by the gravity, two acceleration vectors can be obtained by decomposing $\vec{a}$. The first one is a virtual acceleration that neutralizes the impact of gravity, which is denoted as $\vec{g}$. The other one is the real acceleration, which is denoted as $\vec{a_L}$. According to the characteristics of the gravity, we have:

$$|\vec{g}| \approx 9.8, \quad \vec{a} = \vec{g} + \vec{a_L} \tag{2}$$

Here, $\vec{g}$ indicates the orientation of the device, and $\vec{a_L}$ can be used to track the movement. Fig.4(a) and Fig.4(b) illustrate the components of $\vec{a}$. Traditionally, $\vec{g}$ can be derived by applying a low-pass filter on $\vec{a}$ [12]. The idea is, while the device is moving at a constant speed or at rest, $\vec{a_L}$ is close to 0, and $\vec{a}$ is close to $\vec{g}$. If the variance of $\vec{a}$ is low and $\vec{a}$ is close to $9.8 m/s^2$ in a period of time, the low-pass filter is the most effective method to calculate $\vec{g}$.

Due to the movement of the vehicle or the driver's action, we cannot expect the variance of $\vec{a}$ is always low. When the device is moving at non-uniform speed, the variance of $\vec{a}$ will be high. For example, the variance of $\vec{a}$ of the smartwatch is usually high when the driver is moving his or her hand. To solve this, we apply *Kalman Filter* and leverage the rotation data $\vec{w}$ measured by the gyroscope [29][6][28]. A typical movement can be described as three phrases, which are the start, the moving, and the end. Before the movement starts, the device is at rest, which means $\vec{a}$ has a low variance and $\overrightarrow{g_{before}}$ can be calculated by the low-pass filter as a prior knowledge state. It is the same after the movement ends, and $\overrightarrow{g_{after}}$ can also be calculated as an observed state. The states when the device is moving are hidden. However, the control input for each state is known, which is the rotation of the device, represented as $\vec{w}$. Therefore, the $\vec{g}$ at each certain time during this movement can be calculated by the maximum-likelihood estimation.

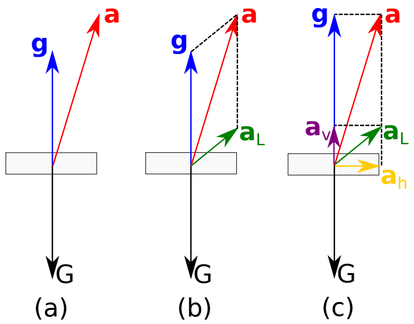

Figure 4: The components of the measurement from the accelerometer. (a) The measurement data a from the accelerometer is always interfered by the gravity G, which causes a virtual acceleration g. (b) a is the sum of g and real acceleration a_L. (c) a_L can be decomposed as a vertical acceleration a_V and a horizontal acceleration a_H.

4.5 Forearm Posture Detection

In a typical driving scenario, the driver's forearm postures will remain unchanged when the driver's hands are holding the steering wheel. As shown in Fig. 5, for a typical driving posture, both the driver's arms will be stretching forward, and the elbows will be naturally lying down, yielding a unique pattern when measuring the posture of the smartwatch wearing on the driver's wrist. When a hand is taken off from the steering wheel, the posture of the forearms is difficult to predict. For example, the hand can hold something (mobile phone, food, etc.) or stay on the leg. However, those postures are rarely same as the posture as when the hands are holding the steering wheel. Thus, in order to detect whether the hands are on the steering wheel, the posture of the driver's forearms can be used as a feature.

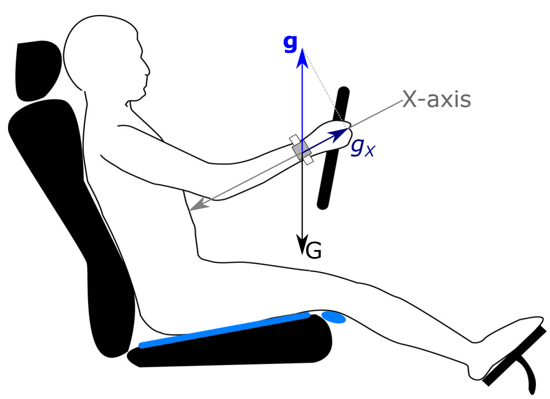

Figure 5: A typical driving posture. The X-axis of the smartwatch is shown is the figure, and the value of g on the X-axis is denoted as g_X.

Since the orientation of X-axis on the smartwatch is always parallel to the forearm, the average value on X-axis of $\overrightarrow{g_{watch}}$ in a window, which is denoted as $g_{X,watch}$, can be used to characterize the posture of forearm. Specifically, different forearm postures will yield different patterns of $g_{X,watch}$ measurements. For example, as shown in Fig. 6, when driver is holding the steering wheel, $g_{X,watch}$ of the smartwatch on the right hand will be around $-3.5m/s^2$. When the driver is holding something in hand, the forearm rises up, and the $g_{X,watch}$ will be around $-8.2m/s^2$. If the driver puts the hand on the leg, the forearm falls downward, and the $g_{X,watch}$ will be around$2.5m/s^2$. To further validate this assumption, we record the driving behaviors of 2 subjects using video cameras and log the trace of $g_{X,watch}$ measured by the smartwatches worn on the driver's wrist. Fig.7 shows the *Probability Density Function* (PDF) of $g_{X,watch}$. It can be seen that $g_{X,watch}$ distributes in a narrow space when the hand is holding the steering wheel.

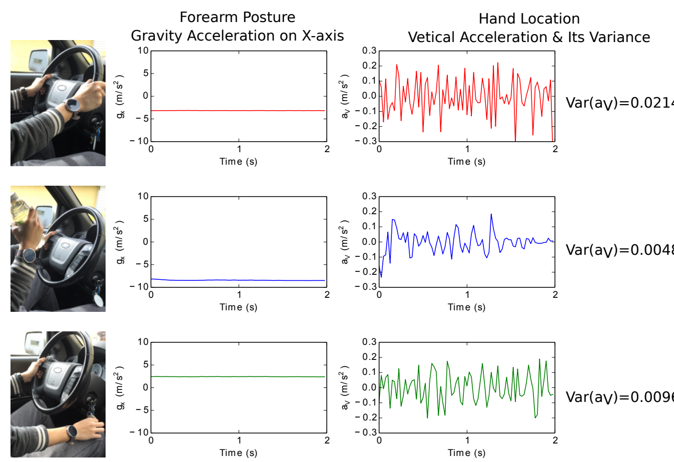

Figure 6: The three typical actions during driving and their motion features. The motion features include g_X and a_V of the smartwatch on the right hand.

4.6 Vibration-based Hand Position Detection

When the engine of a vehicle is on, a continuous vibration along vertical direction will be generated and radiated into the cabin, and then be sensed at the steering wheel and the seat [3]. If the hand is holding the steering wheel, the vibration will be conducted to the driver's wrist, resulting in an increased magnitude of vibration sensed by the smartwatch. Otherwise, vibration conducted to the driver's wrist will be much weaker, because of the significant attenuation when it is transmitted from the seat via the driver's body.

Based on the above observation, SafeWatch leverages the vibration sensed by the smartwatch's accelerometer as another feature for inferring if the driver's hand is on/off the steering wheel when the hand is still. A key challenge in realizing this idea is to address the interfering motion signals introduced by the movement of the vehicle, which is usually orders of magnitude stronger than the vibration signal of interest. SafeWatch addresses this challenge in two steps. First, motivated by the observation that the vibration signal of interest is mainly along the vertical direction, SafeWatch

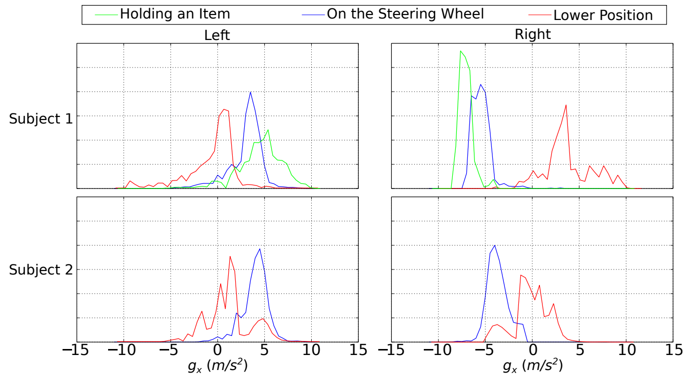

Figure 7: Normalized PDF of $g_{X,watch}$ for three different positions of the hand. (1) Holding an item: the driver is holding something (e.g. a bottle, or a phone) in the hand. Subject 2 does not perform this during our experiment. (2) On the steering wheel: the hand is holding the steering wheel. (3)Lower position: the hand is on the leg or on the seat. This also includes shifting the gear or adjusting the air conditioner.

breaks down the measured signal using the approach shown in Fig. 4(c), and then discards the horizontal component to mitigate the interference introduced by the vehicle's horizontal moves such as acceleration, brake, and turning, etc.. Second, SafeWatch cleans the vertical signal component, by using accelerometer data collected from the smartphone to cancel the interference caused by the vehicle's vertical move such as bumping due to road condition.

Specifically, SafeWatch extracts the vibration-based feature as follows. First, it derives the vertical signal component by computing,

$$a_V = \frac{\overrightarrow{\mathbf{g}} \cdot \overrightarrow{\mathbf{a}_L}}{|\overrightarrow{\mathbf{g}}|}. \tag{3}$$

Second, SafeWatch measures the magnitude of vibration by computing the variance of aV. Third, it estimates the interference caused by the vehicle's movement along vertical direction, by measuring a_V observed on the smartphone. Because the smartphone is placed in the vehicle, its measurement of a_V characterizes the vertical movement of the vehicle. SafeWatch then mitigates interference by computing,

$$R_{a_V} = \frac{Var(a_{V,watch})}{Var(a_{V,phone})}. \tag{4}$$

Fig. 8 and Fig. 9 illustrate the vibration-based feature extraction algorithm based on two real cases. Generally, when the hand is on the steering wheel, $Var(a_{V,watch})$ is slightly larger, as shown in Fig. 8. If the vibration is mainly caused by the movement of the vehicle, $Var(a_{V,watch})$ will be larger than 0.05, and its distribution cannot provide evidence for detecting the hand position. However, if the hand holds the steering wheel firmly, the vertical movement of the wrist will be similar to the vehicle. In this case, we have $R_{a_V} \approx 1$ as shown in Fig. 9, which means the magnitudes of the vibrations captured by the smartphone and the smartwatch are close. For the detection of the hand position, $Var(a_{V,watch})$ and R_{a_V} are both important features.

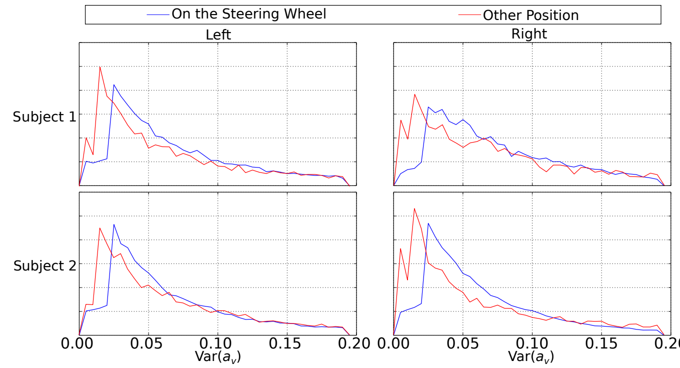

Figure 8: Normalized PDF of $Var(a_{V,watch})$ for subject 1 and 2.

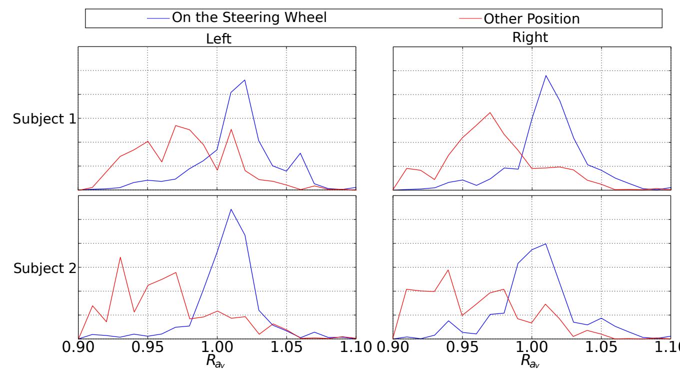

Figure 9: Normalized PDF of R_{a_V} for subject 1 and 2.

4.7 Classifier

The classifier determines if the driver's hand is on/off the steering wheel based on forearm posture and the vibration-based features. Specifically, it builds an vector $\overrightarrow{c} = < g_{X,watch}, Var(a_{V,watch}), R_{a_V} >$ containing three features from previous modules. A training data set is necessary for this classifier. As shown in Fig.10, the feature vector $\overrightarrow{c}$ has a narrow distribution when the hand is on the steering wheel, but it has a board distribution when the hand is away from the steering wheel. We build a training data set that only includes the motion samples when the hand is on the steering wheel. For the test data, the classifier computes the probability of the test data fitting into the distribution of the training data set by the statistical hypothesis testing (e.g. *Welch's t-test* [36]).

4.8 Vehicle Turning Detection and Auto Calibration

A critical challenge for SafeWatch is it requires frequently training, even during one driving trip. The driver may switch the posture, and the smartwatch can be moved to various positions on the wrist. In order to maintain the high accuracy of the classifier, SafeWatch must continually adapt itself into the most recent status. An important observation is the hand must hold the steering wheel in order to turn the vehicle. Thus, the ground truth feedback can be obtained around the moment of turning. In order to detect the vehicle's

Table 1: Information of the experiment

Subject	Watch (Left)	Watch (Right)	Phone	Driving Trips	Total Length of Data
1	Moto 360 2	Moto 360	Moto G	8	132min
2	Moto 360 2	Moto 360 2	Moto G 2	10	125min
3	Sony Smartwatch 3	Sony Smartwatch 3	Moto G 2	4	86min
4	Moto 360 2	Sony Smartwatch 3	Moto G 2	12	124min
5	Moto 360 2	Moto 360 2	Moto G 2	12	118min
6	Moto 360 2	Moto 360 2	Moto G 2	19	179min

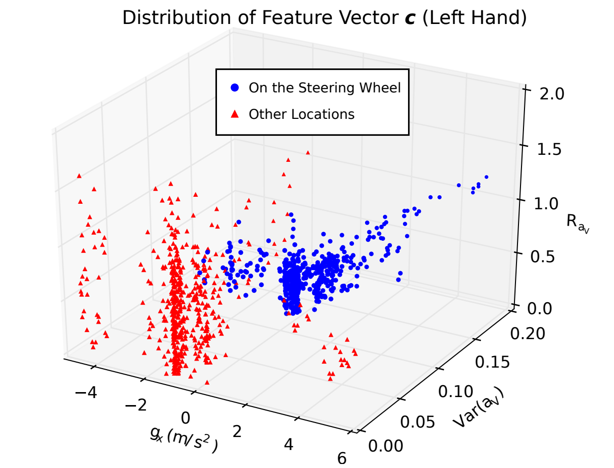

Figure 10: The distribution of feature vector c while driving. When the hand is on the steering wheel, c follows a compact distribution. Otherwise, c distributes widely in the space.

turning, SafeWatch analyzes the data collected by the gyroscope on the smartphone [9]. Specifically, the rotation around the direction of the gravity indicates the angle of the vehicle's turning.

Another question is how the new data should be used to update the original training data set. The two methods are: replacing some of the oldest data or replacing some of the old data with the longest Mahalanobis Distance to the new data. The former idea helps SafeWatch maintaining the most recent training data set following the timeline. The latter idea moves the whole training set closer to the new data no matter each sample is older or newer. The performance of the auto-calibration module with these methods are evaluated respectively in Section 5.2.2.

5 EVALUATION

We evaluate SafeWatch with 75 real driving drips collected from six subjects. Each subject is provided with two smartwatches and one smartphone, all installed with apps that run in the background to record the raw data of motion sensors. In order to obtain the ground truth of driver's hand gestures, we collect location data using the GPS of a smartphone, and then record the driver's hand gestures through video-recording. The details of collected traces are summarized in Table 1.

5.1 Hand Movement Detection

As we discussed in Section 4.3, the performance of detecting unsafe hand movement depends on the choice of L. Fig. 11 shows the accuracy of distraction detection under different values of L. It can be seen that if the hand movement lasts for more than 2.5s, the recall is over 97.1% and the precision is over 91.0%. The detection accuracy further improves when the hand moves for a longer period of time.

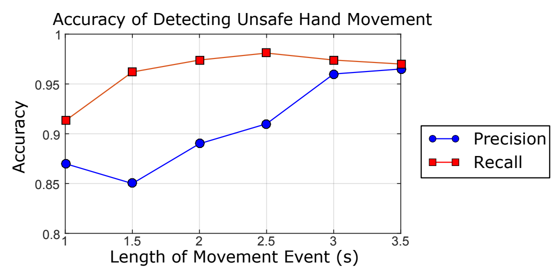

Figure 11: Accuracy of detecting unsafe hand movement with different length of movement event.

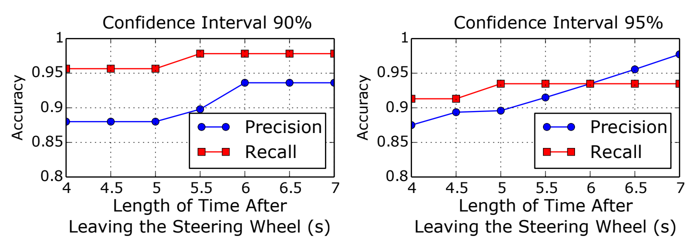

Figure 12: Accuracy of the classifier with different confidence intervals and sensitivities.

5.2 Hand Position Classification

5.2.1 Classification Accuracy. When the driver is still, SafeWatch employs the hand position classifier introduced in Section 4.7 to infer if the driver's hand is on/off the steering wheel. Specifically, SafeWatch classifies hand position by first training a Gaussian model using the approach introduced in Section 4.8, and then applying *Welch's t-test* to check whether the test data collected while driving fits into the trained model. Similar to hand movement detection, the hand posture classification is performed based on sample windows of 0.5s. SafeWatch reports a distraction event if

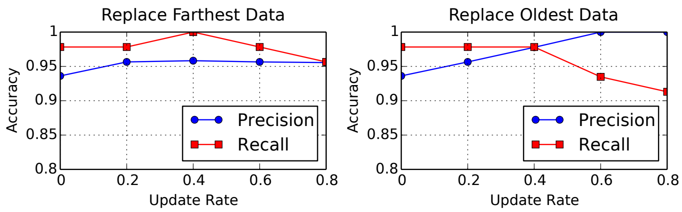

Figure 13: Accuracy of by the classifier with the auto-calibration. The update rate means how many portions of the training data set is replaced with the new data (e.g. update rate = 0.4 means 40% of the training set should be replaced with the new data for each auto-calibration).

the driver's hand is away from the steering wheel for T consecutive sample windows. Fig.12 shows the accuracy of distraction detection for different values of T. As shown in the figure, for T larger than 6s, both of the precision and recall are higher than 90%.

5.2.2 Auto-calibration. If the posture of the driver changes during a driving trip, the training dataset should be calibrated, in order to adapt into the new environment. As we introduce in Section 4.8, the training data set can be updated when the driver is manipulating the steering wheel, by replacing oldest original data or replacing the data with the longest Mahalanobis Distance to the new data. We evaluate how the errors can be reduced with the auto-calibration. The parameters of the classifier are set to 90% confidence interval and 6.0s sensitivity.

The performance of SafeWatch with auto-calibration is shown in Fig. 13. With proper setup, the recall and precision rate can be both higher than 97%. In this case, the errors can be reduced to less than 1.5 per hour. If the auto-calibration process replaces the oldest training data, the distribution of the training data set will extend larger. This method targets to cover more situations of "hand is on the steering wheel", and build a more general model for it. In this case, less unsafe actions will be detected. If the farthest data are replaced in this process, the training data set will have a narrower distribution, and the system will be more sensitive to the unsafe actions. If we replace too much old data to the new data, the training set will overfit the new environment, and more detecting errors appear.

5.3 Micro-scale Driving Behavior Analysis

We next conduct a micro-scale driving behavior analysis using SafeWatch. Fig. 14 shows the detection results along with the ground truth during a 20-minute driving trip, which covers two routes on a city road and a highway. As shown in Fig. 14, based on the analysis of motion data collected on the city road route, SafeWatch discovers a driving habit of the subject when he manipulates the steering wheel, which consists of a sequence of hand gestures including 'turning the steering wheel with the right hand, holding the steering wheel with the left hand, and then turning the steering wheel with the right hand". The left hand is only used to hold the steering wheel, while the right hand is used to turn it. In the highway trace, we observe that the frequency of the subject's hand movements significantly reduces, mainly because there are fewer curves and turns on the road. In this case, the driver's right hand moves less frequently than his left hand. Meanwhile, the right hand tends to stay away from the steering wheel, which implies that the right hand is relaxed. Another observation is that the positions of the hands keep changing throughout the driving trip. For example, both hands are on the steering wheel at the beginning of driving, but they tend to move away from the steering wheel more frequently after the first 3 minutes.

In order to study this in detail, we analyze the outputs of our classifier for different driving trips of other subjects. Specifically, we check how the roads and the driving time impact the driving behavior. Fig.15 shows the driving behaviors of four subjects on different roads. On the city road, the drivers are more likely to hold the steering wheel firmly. The duration of each movement is short, but the frequency is high. The reason is that drivers have to adjust the steering wheel more frequently on city road that has more turnings. We can also observe that the dominant hand moves more frequently than the other hand, because drivers tend to user their dominant hands for operating the steering wheel. SafeWatch also observes that the subjects we study have different driving habits on the highway. For example, Subject 1 and 4 tend to frequently put their non-dominant hands on the leg. Specifically, their dominant hands always hold the top part of the steering wheel, in order to turn it conveniently towards any direction only with one hand. For the most of the time, the dominant hand of a subject is the only hand on the steering wheel, and it rarely moves away from it. Subject 2 and 3 usually use both hands to hold the steering wheel at 9 o'clock and 3 o'clock positions. On the highway, they tend to relax the dominant hands and move them away from the steering wheel, then hold the steering wheel only with the non-dominant hands.

Fig.16 shows the driving behaviors of the subjects along with the driving time. At the first minute of driving, the vehicle usually is being moved out of the parking lot. A series of jobs are completed during this time, such as shifting the gear, adjusting the A/C, playing the music, etc. The hands stay on the steering wheel at the most of the time during the 2nd to the 3rd minute. We assume that the driver just enters a good status, and the alertness is very high at this moment. However, after 3 minutes, the hands begin to move away from the steering wheel, which corresponds to the driver's lower alertness. Another study shows the same observation with the *electroencephalogram* (EEG) monitoring [31].

6 DISCUSSION & FUTURE WORK

Our results show that SafeWatch can log shows most of the subjects' driving habits, such as the favorite position of the hand on the steering wheel. We provide the subjects intuitive summaries of their driving behaviors like "the left hand is more likely to be away from the steering wheel", or "the right hand is more active when turning". Interestingly, most subjects can only partially confirm these, and they are not very confident about what they did during driving. When they reviewed the recorded videos, they expressed that they are not aware of when they moved the hand away from the steering wheel while driving, and they had never considered about their unsafe driving behaviors. This fact demonstrates that SafeWatch can effectively improve the driver's self-awareness of unsafe driving behaviors.

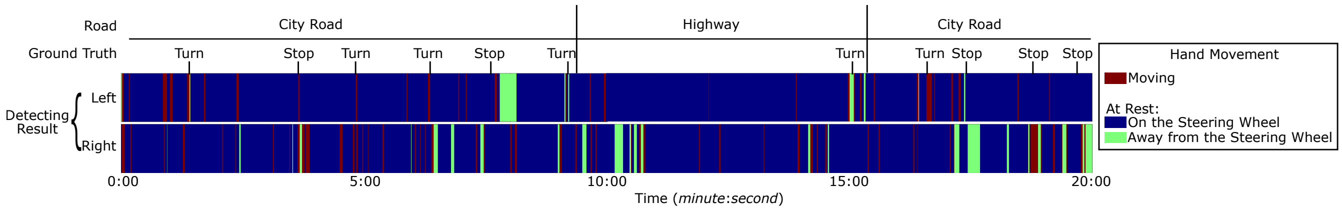

Figure 14: A 20-minute driving trip by Subject 3. The detected actions of the hand are presented. The hand movements shown in the figure include short movements, which may not be detected as unsafe.

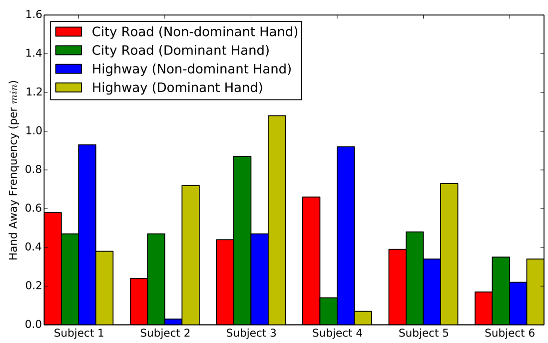

Figure 15: The driving behaviors of the subjects on different roads. The frequency of "hand is away from the steering wheel" for each subject is shown in the figure.

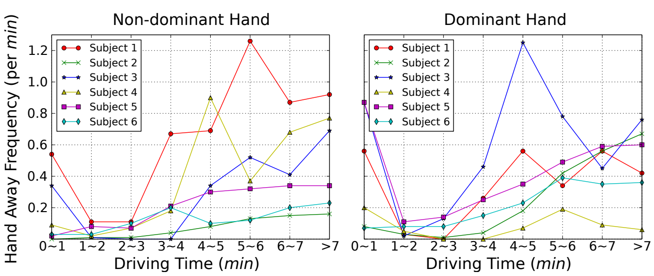

Figure 16: The driving behaviors of the subjects along with the driving time. The frequencies of "hand is away from the steering wheel" are shown in the figure.

Some effective methods were developed to warn the driver for the unsafe behaviors [13]. A common method is to play a ring tone from the smartphone. However, wearables can provide more natural ways of alerting the driver, such as through vibration feedback. Furthermore, we plan to study the effectiveness of such feedback through monitoring the response from drivers. For example, if the motion samples show that the driver's hand returns to the steering wheel after the alert, the alert may be accurate and effective.

7 CONCLUSION

This paper presents SafeWatch – a wearable sensing system that accurately detects driver's hand motions and identifies unsafe driving behaviors. SafeWatch detects whether a driver's hand is on/off the steering wheel based carefully designed features from motion data, such as the posture of the driver's forearm and the vibration of the wrist-worn smartwatch. SafeWatch employs a novel adaptive training algorithm which deals with the significant variation of motion features across drivers, vehicles, and different driving trips. The evaluation with 75 real driving trips from 6 subjects shows that SafeWatch has a high accuracy over 97.0% for both recall and precision in detecting the unsafe hand positions when the condition lasts over 6.0*s*, and over 97.1% recall and over 91.0% precision in detecting the unsafe hand movements when it lasts for more than 2.5*s*.

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