Enhancing Driving Safety via Smart Sensing Techniques

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A thesis submitted to McGill University
in partial fulfillment of the requirements of the degree of

DOCTOR of PHILOSOPHY

August 2018

2018/08/13

Abstract

Drivers' "illegal maneuver" and "unsafe behavior" contribute to a large number of traffic accidents every year, which are now receiving great attention from both government regulators and car manufacturers. Indeed, many research efforts have been dedicated to understanding and recognizing dangerous driving events to prevent crashes and injuries. In addition to the technologies that are already in vehicles, enhancing driving safety via mobile sensing techniques (e.g., smartphones and wearables) is becoming increasingly successful. With the deep penetration of smart computing, the mobile device today equipped with numerous sensors that has become a very effective platform to facilitate various safety applications. In this thesis, we leverage off-the-shelf mobile sensing platforms (i.e., smartphones and wrist-worn devices) to detect and analyze dangerous driving events. Our purpose is to use real-time alerts and long-term feedbacks to increase drivers' awareness of dangerous behaviors, which could help them shape good driving habits and promote safety.

Specifically, two studies are presented: 1. SafeCam - analyzing intersection-related driver behaviors using smartphone sensors, and 2. SafeDrive - detecting distracted driving behaviors using wrist-worn devices (e.g., smartwatch). The first study focuses on the intersection safety which is a critical issue in current roadway systems. In the United States, nearly one-quarter of traffic fatalities and half of all traffic injuries are attributed to intersections. We design SafeCam that uses embedded sensors (i.e., inertial sensors and cameras) on the smartphone to track vehicle dynamics while at the same time adopts computer vision algorithms to recognize traffic control information (e.g., traffic lights and stop signs). The system is able to detect dangerous driving events not only on roads but also at intersections including speeding, lane waving, unsafe turns, running stop signs and running red lights. The second study addresses the distracted driving problem that has been considered as a major threat to the traffic safety. It is estimated that roughly 30% of vehicle fatalities involve distracted drivers, which cause thousands of injuries and deaths every year in the United States. SafeDrive is a driving safety system that leverages the wrist-worn (i.e.,smartwatch) sensors to track driver's hand motion for preventing driver distractions. SafeDrive can detect five most common distracting activities including fiddling with the control (e.g., infotainment systems), drinking/eating, using smartphone, searching items at passenger side and reaching back seats.

In the evaluation, we conduct extensive real-road experiments using different types of vehicles (e.g., sedan, minivan and SUV) and recruiting multiple participants (15 for SafeCam and 20 for SafeDrive). The experiment results demonstrate that both SafeCam and SafeDrive are robust to real-driving environments, which could detect critical driving events and have great potential to educate drivers on how to safely operate the vehicle.

Abrégé

À chaque année, le comportement à risque et illégal de certains conducteurs contribuent à un grand nombre d'accidents de la route, ce qui commence de plus en plus à attirer l'attention du gouvernement et des manufacturiers d'automobiles. De nombreuses études sont axées sur l'identification et la compréhension des conditions routières dangereuses afin de prévenir des accidents. À présent, les dispositifs intelligents tels que les téléphones intelligents et les appareils portables et prêts-à-porter, sont davantage utiles pour augmenter la sécurité routière. Ceux-ci s'ajoutent à de nombreuses technologies déjà incorporées dans la conception du véhicule. Les téléphones intelligents sont munis de nombreux capteurs qui s'avèrent une plateforme utile pour faciliter le développement de nombreuses applications pour promouvoir la sécurité routière. Cette thèse discutera du développement et de l'utilisation de plateformes technologiques à base de capteurs mobiles (i.e. Téléphones et montres intelligents) pour détecter et analyser des comportements de conduite dangereuse. Notre objectif est d'utiliser des alertes en temps réel et de la rétroaction à long-terme pour augmenter la sensibilité du conducteur à ses comportements à risque. Ceci pourrait l'aider à devenir un meilleur conducteur et à favoriser la sécurité sur la route.

Deux études seront présentées : 1. SafeCam – analyse des comportements du conducteur aux intersections en utilisant les capteurs des téléphones intelligents et 2. SafeDrive – surveillance du niveau de distraction du conducteur en utilisant des montres intelligentes. La première étude comporte une analyse du comportement routier du conducteur aux intersections. Ceci s'agit d'un élément critique de la conduite dangereuse, car près de 25% des décès et 50% des blessures sur la route sont reliés aux intersections annuellement aux États-Unis. Nous avons conçu SafeCam, un système qui utilise les capteurs intégrés du téléphone intelligent (i.e. Capteur à inertie et caméras) pour saisir les données sur la dynamique du véhicule, ainsi que pour reconnaitre de l'information sur le contrôle de la circulation (e.g. feux de circulation et panneaux d'arrêt) en utilisant des algorithmes informatiques de vision artificielle. Le système peut aussi détecter des manœuvres routières dangereuses aux intersections telles que le non-respect des feux rouges de la circulation et des panneaux d'arrêts, l'excès de vitesse et couper la voie à un autre véhicule. La deuxième étude adresse la distraction au volant qui se trouve l'une des causes le plus souvent citées dans des accidents routiers. On estime que près de 30% des milliers de décès enregistrés sur la route à chaque année aux États-Unis implique des conducteurs distraits. SafeDrive est un système qui utilise les capteurs intégrés des montres intelligentes pour prévenir les distractions au volant. En suivant

les mouvements des mains du conducteur et en exploitant des algorithmes d'apprentissage machine, SafeDrive peut détecter les cinq sources de distractions les plus communes, dont utiliser avec les contrôles d'un véhicule, manger et boire, manipuler son téléphone cellulaire et chercher des items à l'intérieur du véhicule.

Lors de notre enquête, nous avons effectué des recherches approfondies en conditions réelles en utilisant différents types de véhicules (e.g. berline, camionnette, VUS) et en recrutant de multiples sujets (15 sujets pour l'étude SafeCam et 20 sujets pour l'étude SafeDrive). Les résultats nous démontrent que SafeCam et SafeDrive s'avèrent de systèmes robustes pour évaluer les comportements à risque des conducteurs sur la route et qu'ils peuvent contribuer de manière importante à l'adoption de comportements de conduite sécuritaire par ceux-ci.

Acknowledgement

First and foremost, I would like to express my heartfelt gratitude to my supervisor, Professor Xue Liu for his constant encouragement and guidance throughout my PhD study and all the stages of writing this thesis. I am grateful for the inspiration and opportunities he provided that let me participate in cutting-edge research topics. Without his consistent and illuminating instruction, this thesis work could not have reached its present form.

I would specially thank Professor Wenbo He, since her support has always been very generous in both time and research resources, which helped me overcome many intellectual challenges in my PhD study. I would also thank Professor Xiao-Wen Chang, Professor Jackie C. K. Cheung and Professor Kui Wu for serving on my PhD Thesis defence committee. Their technical and editorial advice and infinite patience were essential for the completion of this thesis, which has greatly improved and clarified this work.

I would also like to thank my collaborators: Professor Guoliang Xing, Mr. Chongguang Bi and Dr. Mingyuan Xia for their distinct contributions in project design, data analysis and delivering impactful research results.

I am grateful for the chance to study and would like to thank all brilliant and professional people in CS department and especially the Cyber-Physical System Laboratory (alphabetically): Jing Chen, Yixin Chen, Dr. Xi Chen (Ms), Dr. Xi Chen (Mr), Dr. Hanqiang Cheng, Shuonan Dong, Dr. Yi Gao, Fei Gu, Dr. Fanxin Kong, Dr. Linghe Kong, Jikun Kang, Peng Kang, Xinye Lin, Xuan Li, Chen Ma, Zhonghao Sun, Qianyuan Sun, Qinglong Wang, Dr. Wen Wang, Dr. Qiao Xiang, Kai Xiong, Xuepeng Xu, Shen Yan, Dr. Yuan Yao, Jianan Yue, Jing Zhang, and Dr. Nan Zhu. For their valuable comments, help, support and suggestions and and all the memorable times in McGill.

Furthermore, I would like to express my greatest gratitude to my family. My degree is at the expense of their sacrices. My beloved wife, Jun Tian, is the one who always stands by my side, sharing my happiness and successes, facing my frustrations and failures together. And I give my deepest thanks go to my parents for their self-giving love and support throughout my life.

And finally, last but by no means least, I would like to thank all persons who have ever supported me during my graduate studies. I wish everyone a happy, healthy and prosperous life. Thanks for all your encouragement!

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Chapter 1

Introduction

Over the past few decades, the number of people driving and using vehicles represents a steady increase in many countries. Along with such trends, the traffic accidents are on the rise every year which resulted in a large number of fatalities and injuries. According to the world health organization, nearly 1.3 million people died and over 30 million injured or disabled in road traffic crashes each year. Drivers' "illegal maneuver" and "unsafe behavior" (e.g., aggressive driving, distracted driving) are considered as the leading cause of the car accidents [4–6]. As reported by the U.S. National Highway Traffic Safety Administration every year over 50% of traffic accidents take place due to unsafe driving problems [7].

Crash data shows that leading factors of traffic accidents include speeding, failure to keep in proper lane, making improper turns, smartphone use, eating/drinking, as well as failure to obey traffic signs, etc. These actions could not only lead to convictions and higher insurance premiums but also cause physical, financial and mental damages for everyone involved in accidents [8, 9]. Unfortunately, most of us always can not realize our unsafe behaviors during everyday driving unless be told by others [10]. In order to promote road safety, governments have enforced laws and legalized local policies to prevent these potentially-dangerous actions, such as increasing fines and introducing demerit points. However, it is still not enough to reduce the the rate of related accidents.

On the other hand, people are found less likely to engage in unsafe driving when there is a monitoring system in the vehicle [11, 12]. The potential effect is two-fold. Firstly, drivers who are aware of being observed may tend to modify their behaviors, and secondly, such systems can alert drivers to dangerous driving situations and provide the feedback of specific issues with recorded events for better understanding. Large-scale field studies have reported an average estimated accident reduction of some 20% as the result of such interventions [13]. Therefore, driver behavior profiling and in-vehicle activity monitoring have become a major research and development priority of both governments regulators and car manufacturers. These kinds of systems can be broadly called Advance Driver Assistance Systems (ADAS), Driver Inattention Monitoring Systems, or Driver Alert Control Systems.

Many research efforts have been dedicated to design and manufacture in-vehicle monitoring systems to understand and recognize dangerous driving conditions. However, most of these systems require additional devices such as cameras and infrared sensors. Moreover, the installation and operation of such typical units may also incur high costs (over $500) [14, 15]. For example, several companies have offered commercial products for fleet management and individual driver monitoring using in-vehicle cameras and sensors, which in average charge over $300 as start-up fee plus $30 monthly fees. As an alternative approach, the assessment of driving behavior through mobile sensing platforms (e.g., smartphone) is becoming increasingly successful in recent years. In contrast, with the deep penetration of smart computing the mobile devices today are equipped with numerous sensors (e.g., inertial sensors and cameras), which are able to collect and identify different types of driving data such as speed, acceleration/braking and turning/cornering, etc. Such mobile sensing platforms are inexpensive, accessible, and effective, thus have enabled a variety of driver safety applications to avoid crashes and injuries. Meanwhile, auto insurance companies also started to encourage customers to enroll in safe-driving programs (e.g., Desjardins [16] and TD Insurance [17]) that use smartphones to monitor and evaluate driver behaviors. The customers with good driving scores will get rewarded with the applicable discounts (up to 25%) on car insurance premium upon renewal.

In this thesis, we leverage mobile sensing platforms (i.e., smartphones and wrist-worn devices) to detect and analyze critical driving events, which aims to raise drivers' awareness of dangerous behaviors and promote road safety. Towards this goal, we use embedded sensors on mobile devices (e.g., smartphone and smartwatch) to track driver motion and vehicle dynamics, while at the same time adopt machine learning algorithms to recognize different driving activities. Specifically, two studies are presented in the thesis: 1. SafeCam - analyzing intersection-related driver behaviors using multi-sensor smartphones [18], and 2. SafeDrive - detecting distracted driving behaviors using wrist-worn devices [19]. We aim to provide both real-time responses and long-term feedbacks on drivers' behaviors, which could help them to shape safer driving habits and thus have great potential to prevent different causes of accidents.

1.1 Enhancing Intersection Safety

As one of the most important parts of the roadway system, intersections are known as planned conflict points where different paths separate, cross and join. There are always vehicles, pedestrians as well as bicycles at intersections making different approaching or turning. Thus it is not surprising that the major challenges of addressing road safety involve intersections. According to the report by the U.S. Department of Transportation [20], over the last several years roughly 25% (nearly 8,000) of the fatalities and an average of 50% (nearly 750,000) of the serious injuries have been attributed to intersections. In addition, intersections can also become very congested when there are accidents happened, resulting in traffic inefficiency and delay that may make drivers/customers dissatisfied or frustrated. Therefore, an urgent need arises to understand the factors that lead to intersection accidents.

When an intersection-related crash occurs, it involves at least one vehicle which was engaged or should have been engaged in making an intersection-related manoeuvre (e.g., turn). The accidents could be harmful to the vehicle, drivers and occupants, as well as vulnerable road users [21] (e.g., pedestrians and bicyclists). Diverse strategies have been deployed to enhance intersection safety. However, many intersection safety solutions are engineering based such as road markings and traffic control devices (signs and signals), which do not consider the effects of human factors (i.e., how drivers operate the vehicle, the movements of pedestrians or bicycles).

Statistical studies have shown that a large number of accidents at intersections were caused by drivers' violations or errors [22,23] such as perception failures (e.g. inattention), situation misunderstanding (e.g. misjudging the pedestrian), and wrong decision (e.g. incorrect maneuver). Though some intersections already have speed radar or red-light cameras installed, the coverage of these devices is still not large enough (especially in United States and Canada). Moreover, such devices only target on one or two specific driving events which is less practical. On the other hand, there have been a number of approaches focusing on sensing traffic participants [24] such as pedestrians, bicycles, as well as other vehicles, etc. Since many accidents occur when a vehicle passes the intersection with these unforeseen participants that approach/cross suddenly from the opposite lane [23,24]. Both on-board and road-side systems are presented, however, they are either limited by sensing range or too expensive to be widely deployed. Moreover, such approaches do not consider driver behavior analysis that can not provide prompt responses to alert drivers before they made errors. Therefore, a combination of strategies that focuses on not only traffic control but also driver behavior is needed to truly solve the problem.

Moving along this direction, we present SafeCam, a smartphone-based driving safety system that targets intersection-related unsafe driver behaviors. SafeCam utilizes smartphone inertial sensors (i.e., accelerometers, gyroscopes and GPS) and the rear-facing camera to track vehicle dynamics and recognize traffic control information (i.e., stop signs and traffic lights). By using the sensing data and adopting the computer vision algorithms, the proposed system is able to detect different driving conditions and analyze driver on-road behaviors such as how the driver passes/stops at the stop signs and red lights, whether the driver makes unsafe turns, any speeding or lane drifting issues when crossing intersections. In addition, SafeCam is capable of providing both real-time unsafe driving alerts and long-term driving behavior analysis to help make intersections safer.

1.2 Preventing Distracted Driving

Accumulating evidence has shown that distracted driving is a principal factor in driver inattention, which can result in driving errors and cause a large amount of fatal accidents and serious injuries [25]. Over 3400 people were killed and approximately 391,000 injured in motor vehicle crashes every year in the United States involving distracted drivers [6, 26]. Organizations such as National Highway Traffic Safety Administration (NHTSA) and Federal Highway Administration (FHWA) are partnering with the goverments and local police to against distracted driving and educating people to raise awareness of its dangers. Actually, we engage in a number of driving non-related tasks on road every day. Most of these tasks are distractions which are potential dangerous and may increase the risk of crashing. However, many distracting events are inapparent that we can hardly be aware of them. According to the study [27,28], drivers always fail to notice that they are distracted while driving (unless someone told them). Therefore, it is desirable to build a in-vehicle system that monitors drivers' distracted behaviors, sending alerts and helping them to reduce the risk of accidents and promoting safe driving practices.

Recently we can see significant advances in preventing driver distractions using in-vehicle cameras and infrared sensors [29,30]. The commonality of these systems is tracking driver's eye state and head positions to determine whether the driver is focusing on the road ahead. Similar safety features can also be found in today's cars with high-tech packages. However, these systems require specialized infrastructures that incur additional costs (we have to pay for the "premium package".). On the other hand, great efforts have been made to exploit smartphone sensors (e.g., inertial sensors and cameras) to detect dangerous driving conditions such as drowsy/inattentive driving (eye tracking), careless/aggressive lane changing [31,32], etc. Nevertheless, the feasibility of such systems is inevitably limited by several constraints. For example, the system may fail to recognize driver's eyes or face due to various lighting conditions (e.g., strong sunshine, dark night) or the phone is not properly mounted in the vehicle. More importantly, a driver can be distracted even his/her glance is inside the FRD (field relevant for driving). Since they want to keep eyes on road, while use their hands to handle non-driving tasks with less eye contact. Existing systems that use smartphone inertial sensors can only provide detection results after the specific driving activity finished [28,32,33], which are less efficient for preventing driver distractions.

Several known approaches exist for driving safety that detect whether the driver's is holding the steering wheel or not [1, 34, 35] . In our prior work, we addressed this problem by exploiting wrist wearable sensing to track driver hand motion and forearm postures. More difficult, however, is determining whether a driver is actually participating an unsafe distracting activity or performing a secondary task[1] to improve driving performance. Distinguishing different types of driving events could assist the system to make a proper response: alert driver immediately or over a specific period of time (e.g., three seconds). It can also help raise drivers' awareness of their unsafe/bad driving behaviors, and thus shape good driving habits to avoid car accidents.

Moving along this direction, in this paper we propose SafeDrive, a low-infrastructure approach that leverages wrist-wearable sensing techniques to prevent driver distractions. SafeDrive uses inertial sensors on the wrist-worn device (smartwatch) to track the driver's hand (right) motion while at the same time adopts machine learning algorithms to determine whether the driver is distracted. The system is designed to detect most commonly occurring events that may result in distracted driving [6] including fiddling with the control (e.g., infotainment systems), drinking/eating, smartphone use, searching items at passenger side (front) and reaching backseat. SafeDrive does not require any specialized infrastructure which overcomes the limitations inherent in the existing approaches. Thus it is a lightweight driving safety application that alerts and assists the driver in terms of both safety and convenience.

1.3 Objectives and Contributions

To enhance driving safety, we propose two smart sensing systems SafeCam and SafeDrive to understand and analyze driver behaviors. In this section, we discuss the objectives of these two studies and summarize the contributions of our research.

[1] In order to distinguish different tasks, the driving activity is commonly split into two or three classes such as primary, secondary and tertiary tasks [36].

1.3.1 Objectives

SafeCam - Analyzing dangerous driving events at intersections

The system is designed to address intersection safety, we focus on the critical driving events that most commonly occur at intersections including running stop signs, running red light, unsafe turns, hard acceleration/braking and speeding. SafeCam should be able to detect traffic control signals such as traffic light and stop signs, while at the same time track vehicle dynamics to identify different driving conditions. Although the smartphone is becoming more and more powerful, the computational cost of vision-based application is still high. As the driving event detection is time sensitive, a long image processing delay may lead a miss on event detection. There are always trade-offs between effectiveness and efficiency and we need to improve detection accuracy considering both factors. In addition, the vision-based detection can be easily affected by lighting conditions (e.g. sunshine and cloudy weather), unpredicted noise (e.g., vehicle vibration on bumpy road) and non-related objects (e.g., vehicle taillights). Thus, a lightweight system design which is robust to real-road environments is desirable. The detailed design is presented in Chapter 3.

SafeDrive - Preventing driving distractions

SafeDrive aims to detect driver in-vehicle unsafe behaivors for preventing driving distractions. While the idea of utilizing wrist-worn device to track hand motion seems simple, many challenges arise in the implementation. Firstly, the driver's behavior may not be a transient but consecutive action [28]. Drivers have different gesture styles (e.g., direction and speed) which would result in imprint personal hallmarks [37]. Thus it is difficult to build a robust classifier for all drivers when we only have limited samples (participants). Secondly, unlike existing recognition scenarios [38,39], in the driving cases the sensory data collected from the smartwatch contains vehicle's motion (e.g., acceleration and vibration), which is noisy and cannot be directly used to represent driver hand movements. Thirdly, SafeDrive should be able to trigger the alert as soon as possible if a dangerous driving event is detected. Due to limited processing power, we need to balance the transmission and processing tasks between the wrist-worn device (e.g., smartwatch) and smartphone. The system design of SafeDrive is presented in Chapter 4.

1.3.2 Contributions

We highlight our main contributions as follows:

Contribution 1. We propose a driving safety application SafeCam, which considers both the driving dynamic and traffic control conditions to study intersection-related driving behaviors. It adopts computer vision techniques to recognize red lights, stop signs and lane markings, while at the same time leverages smartphone sensors to track critical driving events at intersections. The system is able to detect and record intersection most commonly occurring unsafe events including stop signs/red light infractions, unsafe turns, speeding and lane drifting problems. All the sensing data and results of vision-based detection are stored on user's phone. The user fully controls the data and the storage overhead of SafeCam is significantly small compared to the offline video recording solutions.

Contribution 2. To improve the system efficiency and decrease the frame processing workload, we design and implement a series of schemes. We first utilize the image down-sampling method to make a trade-off between the image quality and system delay, then filter out the noisy frames and enhance the object saturation value by considering different road and lighting conditions. Moreover, we leverage location information and driving dynamic data, at the same time use computer vision methods (e.g., neighbour frame merging) to achieve a high detection rate in real-time driving. In the evaluation, we conduct well-designed real-road driving experiments, involving 15 drivers and 6 cars in an urban area. The experiment results demonstrated that SafeCam is robust and effective in real driving environments and has great potential to promote driver safety. In addition, we have a number valuable findings, such as, drivers may take longer braking time when they approach a stop sign than a traffic light (red/yellow), and most of the drivers (11 out of 15 participants in our test) have lane drifting problems, etc.

Contribution 3. We present SafeDrive, a low-infrastructure smart sensing approach for preventing driver distractions. SafeDrive leverages commodity wrist-worn devices (smartwatch) track driver hand motion while at the same time use smartphone sensors to generate soft hints to detect unsafe driving behaviors. To filter out vehicle interference (acceleration/vibration) and non-gesture movements, we design and implement the algorithms that spot and recognize in-vehicle hand gesture patterns by piggybacking on vehicle dynamic sensing under real-road driving conditions. In addition, to help driver wear the device correctly, we determine the smartwatch position (on right or left hand) by estimating the steering wheel rotation.

Contribution 4. We provide a KNN-SVM classifier and deploy a semi-supervised mechanism to update the training dataset, which improves the detection accuracy and reduces the false positive rate. We design the model to detect driving distractions at the early stage by considering driver arm postures and wrist rotations. We also conduct extensive real-road driving experiments, involving 20 participants (10 males and 10 females) in downtown Montreal with a length of 8 km urban road. SafeDrive achieved an average accuracy over 90% on driver behavior recognition. The experiment results demonstrate that SafeDrive is robust and effective in real-driving scenarios, which is able to understand different types of unsafe driving conditions and alert drivers properly. Thus it has great potential to help drivers shape good driving habits and avoid accidents.

1.4 Thesis Organization

The thesis is organized as follows:

In Chapter 2, we place our work in the broader context of enhancing driving safety and using mobile sensing platforms to monitor driver behaviors. We first review the early work on driver assistance systems, and then discuss the related research on driving behavior analysis for enhancing intersection safety and preventing driver distractions. We present the drawbacks of the existing studies and demonstrate the advantages and novelty of the approaches, algorithms, models and frameworks proposed in this thesis.

In Chapter 3, we present the first study SafeCam. We first give a brief overview of the intersection safety issues and discuss the critical driving events that we focus on in this study. We then describe the design considerations of implementing the SafeCam application on resource limited smartphones and challenges of real-road vision based detections. We then provide the overview of system design and implementation details of SafeCam including driving dynamic sensing, core detection algorithms, and driving event recognition. Finally, we perform extensive evaluation of our system in real-road driving environments involving 15 participants (5 females and 10 males) and 6 vehicles in the city. The discussion about how this work can be extended and potential solutions to improve the system performance are also presented.

In Chapter 4, we introduce the second study SafeDrive. The background and motivation is presented to show the necessity of our proposed system. We discuss the challenges in hand motion sensing and system implementation. Five distracted driving scenarios are defined along with the design considerations. We then present the SafeDrive architecture and implementation details of the system. Four key components of SafeDrive are provided: (1) driving dynamic sensing; (2) hand motion sensing and gesture spotting; (3) hand gesture classification and (4) distracted driving event detection. We conduct extensive real-road experiments involving 20 participants (10 males and 10 females) and 5 vehicles (a sedan, a minivan and three SUVs). We evaluate our system based on several machine learning metrics and discuss the results from user studies. In the end, we address the limitations in the presented work, and talk about the extensions can be deployed in SafeDrive for further development.

In Chapter 5, we conclude this thesis and provide a general discussion of the findings from these studies and a brief idea about the future work.

The contribution of authors is presented in Appendix A, and the author publications are listed in Appendix B.

Chapter 2

Related Work

In this chapter, we review the related work on driver safety study and driving behavior analysis, and discuss how this thesis advances the state of the art. We first present the existing driver safety/assistance applications and studies, so as to confirm the feasibility of utilizing sensors on mobile devices to detect different driving conditions, and demonstrate that the research on driving behavior analysis is critical and necessary. We then discuss the related research and in-vehicle systems on enhancing intersection safety and preventing driver distraction. With a comprehensive understanding of related papers and systems, we present the discussions on drawbacks of the existing studies and demonstrate the advantages and novelty of the approaches, algorithms, models and frameworks proposed in this thesis.

2.1 In-Vehicle Driver Assistance Systems

In order to reduced the number of crashes and fatalities, many changes have been made in legislation combined with an increased use of onboard safety systems [40]. Today's vehicles incorporate a combination of passive and active safety features. Vehicle passive features such as air-bags, seat belts, etc. which are designed to protect vehicle occupants once a collision occurs. Vehicle active safety features include auto braking, following distance estimation, collision avoidance, etc. which function to prevent collisions and reduce the risk of accidents. These systems/features use exteroceptive sensors to identify dangerous driving conditions and either alerts the driver or act on the vehicle. Though such systems are a major progress in traffic safety, the costs and complexity limit their effectiveness.

With the development of smart computing and sensing technologies, a new level of intelligence and intervention has surfaced in the form of systems commonly referred to as Advanced Driver Assistance Systems (ADAS) [41–43], Driver Monitoring Systems [44], and Driver Alert Control Systems [45, 46]. These systems aim to help the driver in the driving process (e.g., automotive night vision, lane departure warning, head-up display, etc.), with the goal of engendering an overall increase in road safety for everyone [47–49]. Though the cost of safety technology is dropping, many of these advanced features are only seen on a limited percentage of cars (luxury/high-end cars or car with premium packages) on the road. In addition, since driver's "illegal maneuver" and "unsafe behavior" have been considered as the leading cause of car accidents [4, 6], driver behavior monitoring is still a very challenging task.

Some companies also offer products for driver monitoring (individual use) and fleet management [50,51], however, most of them need specialized installations with high startup and maintenance fees, and thus reduce the chance of adopting the approaches quickly among a large number of users. For example, a driver monitoring system is presented in [14] which involves three cameras, a two-axis accelerometer and a GPS receiver attached to a compact PC. The system is able to determine the driving environments (freeway or city) and detect erratic driving, braking/acceleration, as well as high speed turns. It is functional but large and costly (over $2000), which makes this an infeasible option for individual drivers. Similarly, another fleet management system DriveCam has multiple sensors, while its price is over $500 per unit with $30 monthly fee, and the company requires a minimum of 20 units to order [15].

Recently, smartphone sensing platforms are becoming more and more popular. Smartphones are easy accessible and cost-effective that obviate the need for specialized in-vehicle hardwares. Academics, companies (e.g., insurers), and other interest groups have developed and released a broad array of smartphone based systems in the field of driving safety study [13,52,53]. Some early work mainly focuses on using smartphone embedded sensors to monitor road surface conditions and sense vehicle dynamics. Systems like Nericell [54] and Wolverine [55] are designed to monitor road and traffic conditions. They use accelerometer, GPS and magnetometer sensors in the smartphone to detect the large acceleration perpendicular to the road surface when the vehicle passes bumps or potholes on the road, while track vehicle braking events to predict traffic states. In addition, White et. al. [56] present WreckWatch, a system to eliminating the delay between accident occurrence and first responder dispatch, which uses the accelerometer and microphone on smartphone to sense when traffic accidents occur (e.g., car crashes) and immediately notify emergency personnel.

Besides, broad usage of smartphones also enables a variety of mobile applications to identify different driving maneuvers and to improve driver efficiency. The aim of these systems is to warn the driver when the situation becomes dangerous and make sure that the driver has all necessary information for coherent decision making. Li et. al. [57] describe a smartphone based trip analysis system. The system could identify the travel mode and purpose of the trips sensed by mobile devices, provide both individual trip summaries and insights to regional travel demand analysis. It generates meaningful patterns that would support traffic operation planning and transit system design.

Some driver profiling systems [58–60] use smartphone sensors to record risky driving events and driver habits, which can be used in fleet management, insurance premium adjustment, energy consumption optimization or carbon emission reduction. To help drivers improve fuel efficiency, Araujo et. al. [61] developed a smartphone application that combines CAN-bus information (using an OBD-II transmitter). The system could provide some useful hints such as switch off the engine, to shift gears earlier or to braking time selection. Furthermore, Dai et.al. [62] propose a system addresses drunk driving issues by utilizing the accelerometer and orientation sensor. To identify a drunk diving event, they compare the sensor reading (vehicle dynamics) with typical drunk driving patterns extracted from real driving tests.

In order to analyze unsafe driving styles, Johnson et. al. [12] introduced an in-vehicle monitoring system, MIROAD, to detect driver aggressive actions. MIROAD fuses the sensing data from smartphone (accelerometer, gyroscope and GPS units) into a single driving pattern classifier and use the Dynamic Time Warping (DTW) algorithm to track multi-types of driving events including turns, lane changes and excessive speed. Comparably, Eren et. al. [63] designs a car-independent system on smartphone based sensing platforms. They deploy a Bayesian classification scheme to propose a deep study on driving habits and label how risky or safe the driving habits of the driver. Fazeen et. al. [64] aims to provide feedback after monitoring drivers in order to effectively correct bad driving behaviors and shape good habits. Based on the collected data, they can record driving events including acceleration, braking and lane changes. However, the smartphone needs to be carefully fixed (in predefined positions: parallel to the floor, with the top of the device pointing forward) in the vehicle, which limits the usability of the system, since a slight modification of the smartphone orientation (e.g., device vibration) would considerably impact the detection performance.

In addition to being a hot topic of academic research, many auto insurance companies [16,17,65,66] also offer driving safety applications to their customers. Such applications will monitor users' driving behaviors such as speeding, hard acceleration, hard braking and unsafe cornering. Customers are motivated by the promotion that they can get rewarded with the discounts (e.g., up to 25%) on next year premium renewal if their driving scores are good. Above systems and approaches show that the mobile sensing platforms have the capability of detecting different types of driving events, which can be further used to enhance intersection safety and prevent distracted driving.

2.2 Enhancing Intersection Safety

As a major challenge for driver-assistance systems, intersection safety is an arena of active research [67]. Many algorithms and approaches have been proposed to help drivers improve ability to see traffic signals at intersections to increase road safety [68]. The most intuitive ways are using rules associated to the context as the basic method to detect unsafe situations [69]. For example, a vehicle is reaching an intersection, the driver should keep a safe speed. Some algorithms available in the literature are mainly based on the estimation of the time remaining before a collision between two objects which are called Time To Collision (TTC) [70, 71]. Alerts are usually given as soon as the TTC becomes lower than a threshold. The main problems of these approaches are the difficulty to take uncertainties into account and rules will become interleaved in complex conditions.

Cao et al. [72] implementes a real-time stop sign recognition system on a Field Programmable Gate Array (FPGA) platform. The system extracts Histogram of Oriented Gradient (HoG) features and uses integral map for fast calculation. This FPGA platform is efficient and capable of supporting a reliable stop sign recognition [73, 74], which can also be extended to detect pedestrians and other objects on road. Meanwhile, as the traffic light recognition is a special perception problem, Google employs a prior map to improve the system performance [75]. They adopt vision-based algorithm to recognize traffic light states on real-time and utilize the prior map information to anticipate the location of the traffic lights. The system has successfully provided reliable traffic signal information during thousands of trips. However, both these two systems require external devices such as digital camera, display screen and processing computer, which increase the installation cost and complexity, thus cannot be widely deployed in passenger vehicles.

By leveraging the smartphone camera, Lai et. al. [76] present a traffic sign recognition scheme for intelligent vehicles. They achieved a high detection accuracy (about 98%) by considering object color and shape features, and then an OCR (optical character recognition) method is used to determine the match to actual targets. But the system still needs a in-vehicle computing device (e.g., compact PC or laptop) for image processing and object recognition tasks. Tucker et. al. [77] introduce an Android application, StopWatcher, to detect damaged or obstructed stop signs. They manually record stop sign location and use GPS data to estimate the distance between stop signs and the target vehicle. It is time consuming to build a database offline and the GPS performance is less stable in the city.

On the other hand, in order to increase driver awareness of unsafe situations before arriving to the intersection, several systems are provided using inter-vehicle communication technologies to avoid car accidents [40, 78–82]. Their basic idea is using vehicle-to-vehicle communication to exchange the absolute position obtained from GPS with each other. Since the positioning accuracy of GPS is sometimes degraded in urban areas in which usually suffered from radio shielding and scattering [83]. In the case of vehicles, researchers leverage initial sensors (e.g., accelerometer and gyroscope [84]) to improve the estimation accuracy. However, since drivers and other traffic participants such as pedestrians and bicycles are equally responsible for accidents that occur. As a result, the system is hard to satisfy a requirement of positioning accuracy since they are not equipped with the same devices [85].

Many on-board sensing systems use cameras or radar to detect pedestrians and bicycles [86, 87]. Furthermore, Fuerstenberg et. al. [88] use laser sensors for detecting obstacles in front of the vehicle, and applied this system to intersection safety study. Other work [89, 90] utilize stereo-cameras and monocular cameras to determine whether the obstacle is pedestrian or not. Such systems could help the ADAS/driver to obtain a relative position of the traffic participants existing in surrounding. However, onboard-sensors on vehicles cannot detect Non-Line-of-Sight (NLOS) objects which are occluded by other vehicles or building. To handle such issues, road to vehicle cooperative systems were developed to narrow down the NLOS spot by using infrastructure sensors such as cameras or millimeter wave sensors setting in high altitude. For example, field tests of collision warning systems at intersections are conducted in California [91] and Minnesota [92]. In Japan, field test of collision warning system in intersections was done in Tokyo [93]. However, the infrastructure sensors are much more expensive than on-board sensors.In addition, some low-cost positioning systems using wireless sensors are also becoming popular [94, 95]. In order to reduce the NLOS spot compared to other on-board approaches, Hisaka et. al. [24] install four wireless communication devices in the four corners of the vehicle, which can roughly detect positions and motions of traffic participants having transmitter by comparing receiving intensities.

Moreover, besides understanding vehicle surroundings, there are studies addressing driving safety issues by detecting how a vehicle is steered, which can be used to prevent unsafe driving behaviors at intersections such as swerving, understeer or oversteer, as well as lane waving, etc. Several models are introduced by [96, 97] that calculate the steering wheel turning angle to predict unsafe driving conditions (e.g., lane change maneuvers). However, these systems need the steering wheel angle data, which not readily available. Lawoyin et. al. [98] propose a low-cost accelerometer-based method to actively monitor Steering Wheel Movements (SWM). They use mounted kinematic sensors and deploy adequately trained Support Vector Machines to estimate the steering wheel turning angle. This technique still relies on external sensors and may cause distraction (sensors are mounted on the steering wheel).

Without using additional infrastructure, Chen et. al. [31] develop V-Sense, a vehicle steering sensing middleware on smartphone to detect various vehicle maneuvers, including lane changes, left/right turns, U-turns, and driving on curvy roads. However, the detection accuracy of V-Sense is limited since it only involve smartphones to capture vehicle dynamics, which can not reflect the steering motion directly. To alleviate these problems, Karatas et.al. [35] present a fine-grained steering tracking approach by utilizing wrist-worn devices (e.g., smartwatch). The system is able to record the dangerous steering wheel motions (understeer or oversteer, hands off the steering wheel), which can be used to facilitate many driving safety applications.

A related approach to our proposed system, Koukoumidis et. al. [99] present a collaborative sensing system, SignalGuru, which detects and predicts traffic signals using the windshield-mounted smartphones. To improve the detection accuracy, it deploys the traffic signal detection algorithm based on basic features of bulbs (color, shape and collocation information) and leveraged the collaborative sensing data via different nodes (smartphones). However, such collaborative scheme requires most of the nodes to be online. It is hard to benefit from the system if there is only one user in the network. In addition, the traffic signal perception in a moving vehicle has not been well examined (most vehicles in SignalGuru were waiting at intersections) and the system has a high processing delay (the average frame processing time is 2 seconds), which is not practical in real-road driving environments. More importantly, dangerous driver behaviors are major threats to intersection safety, while there is less discussion in existing approaches.

2.3 Preventing Driving Distraction

In order to promote road safety, there has been active research and development work on detecting dangerous driving behaviors, especially for the driver distraction/inattention problem [100–105]. Many existing systems leverage smart sensing techniques to determine whether the driver is focusing on the road ahead [106–108] by using real-time vision based algorithms to track drivers' eye state and head positions [109–111]. These systems and studies detect the driver's status based on pre-deployed infrastructure including cameras, infrared sensors, and EEG devices, as well as other inertial sensors [33, 112, 113].

Products like Saab Driver Attention Warning System [114] utilizes two miniature infrared cameras (one at the base of the driver's A-pillar and one in the center of the main fascia) to track driver's eyes. It alerts driver by using a combination of text and voice messages, or vibrations in the seat cushion, as soon as the risk of inattention (e.g., the driver is not looking at the road ahead) is detected. Bhowmick et al. [30] propose an approach that deploys one infrared camera system to classify the eye status (closed or open) for driver drowsiness detection. They first use Otsu binary method to extract the face region, and then locate the facial landmarks to carry out accurate eye tracking. The eye status is identified using nonlinear support vector machine based on the eye shape features. Carsafe [32] introduces a smartphone based dual-camera system that focuses on driver distractions and drowsiness. By using computer vision and machine learning algorithms, Carsafe is able to detect several common unsafe driving events including drowsy driving, inattentive driving, tailgating and lane weaving/drifting during lane changes.

Over and above that, some systems target on one specific driving event (e.g., using smartphone [115]) that may cause driver distraction. Yang et. al. [116, 117] introduce an acoustic ranging system to identify the location of a smartphone is being used in the vehicle by using its audio infrastructure. Wang et al. [118] present an approach that leverages smartphone sensors to manage the distraction problem caused by driver phone use. They employ accelerometers and gyroscopes to capture centripetal acceleration differences due to vehicle dynamics. Based on angular speed and acceleration readings, the system is able to locate the target phone (at driver side or passenger side) and determine whether the driver is distracted. In addition, Chu et.al. [119, 120] introduce a driver detection system (DDS) by utilizing multiple sensors (including accelerometer, gyroscope, and micro-phone) in smartphones. The system is able to determine whether a smartphone user is actually a driver or a passenger in the vehicle based on the detection of specific movements, such as entry swing, seat-belt fastening, or pedal press using inertial phone sensors. Another two smartphone applications, iOnRoad [121] and Augmented Driving [122] provide following distance and lane marker detection, which sends warnings to drivers when they perform the improper following and lane waving.

On the other hand, several smart wheel systems use specialized devices [1,34,123] (e.g., linear potentiometers embedded in the steering wheel) or wrist wearable sensors [35] to monitor driver's hands positions and send alerts when a driver is not holding the wheel. Our prior work, SafeWatch [2] addresses the same problem by tracking driver hands motion to detect driving distractions. We use features such as vehicle vibration and the posture of the driver's forearm to infer the location of hands in the vehicle. Although these approaches and systems are efficient at determining whether driver's hands on or off the steering wheel, they do not analyze and classify the driver behaivors (after hands off the wheel) and thus fail to distinguish different in-vehicle tasks. Since the driving activities are commonly split into two or three classes such as primary, secondary and tertiary tasks [36]. The recognition of different types of driver behaviors could help the system to make the proper response to improve driving performance while minimize distractions to drivers at the same time.

Towards the most related work in detecting driver distraction, Gao et al. [28] presents an acoustic-based approach using audio signatures to recognize in-vehicle inattentive driving events. They utilize the smartphone speaker and microphone to collect unique patterns on Doppler shifts of audio signals caused by driver motion [124]. The system is able to recognize four basic inattentive driving events accurately, however, the performance of audio signature-based approach may become worse due to subtle changes in the environment (e.g., a passenger in/out the vehicle) and require a large amount of calibration effort. Besides, computer vision based model is another well developed solution to driver behavior analysis [125, 126]. These systems use mounted cameras to track driver's hand and recognizes different hand gestures based on captured images. However, they are either easily constrained by various lighting conditions (e.g., strong sunlight or at night time) [32, 127, 128] or need additional infrastructure (e.g., processing devices) to be installed correctly (at the right position) in the vehicle [129–131]. Recently, WiFi distortion based approaches [132] and dedicated sensors [133] are gaining popularity in the field of gesture recognition. Unfortunately, it is less practical for drivers to carry out those hardwares or dedicated sensors in everyday driving.

Different from the existing work, in this thesis, we explore two lightweight sensing approaches that recognize unsafe driving behaviors to address intersection safety and prevent driving distractions. The first approach, SafeCam aims to detect dangerous driving conditions at intersections, it uses smartphone embedded sensors to track driving dynamics (e.g., acceleration, braking, turns) while at the same time adopts vision-based algorithms to recognize different traffic control information (e.g., red lights, stop signs). The second approach, SafeDrive is designed to monitor and understand in-vehicle driver activities, it leverages wrist-worn devices (e.g., smartwatches) combined with smartphones to track driver's hand motion and recognize dangerous distracted driving events (e.g., drinking/eating, searching items, smartphone use). Unlike recent approaches that use wearable sensors for human gesture recognition [37, 134, 135], our project is the first application that targets driver in-vehicle behaviors under real-driving/road circumstances. Moreover, both two proposed systems are capable of real-time driving event recognition and long-term driving behavior analysis.

The primary goal of our research is to develop safety indices that allow automotive engineers, road planners, and other practitioners to proactively prioritize their approaches with respect to driver and pedestrian safety.

Chapter 3

SafeCam: Analyzing Intersection Related Driver Behaviors using Multi-Sensor Smartphones

This chapter is reproduced from the following published article, with the permission from IEEE:
Landu Jiang, Xi Chen, and Wenbo He. "SafeCam: Analyzing intersection-related driver behaviors using multi-sensor smartphones", In Pervasive Computing and Communications (PerCom), 2016 IEEE International Conference on, pp. 1-9. IEEE, 2016.

3.1 Overview

3.1.1 Motivation

Intersection safety has been a national, state and local priority. According to the study [136], approximately 2.5 Million intersection accidents are reported in the United States every year. Most of these crashes/collisions involve drivers' "illegal maneuver" or "dangerous behavior" such as unsafe turns, speeding and running red light, which have been considered as major threats to the traffic safety. As a result, both public and private organizations such as FHWA (Federal Highway Administration), NHTSA (National Highway Traffic Safety Administration), ITE (Institute of Transportation Engineers), as well as AAA (American Automobile Association) continue to develop and deploy strategies to make intersections safer.

Though there have been a number of driver safety applications that leverage mobile sensing platforms to recognize and monitor different driving conditions [12, 13, 137], the intersection safety issues are still not well investigated yet. One major reason is that the traffic at an intersection is controlled by various road signs, lane markings and traffic signals. The traffic control information is a key component to the system to understand different driving events. However, existing approaches do not consider the perception of real-time traffic control information, thus they are not able to detect and track intersection-related driving behaviors. Although the traffic control devices and signals can be obtained from the offline video, the system needs extra storage and will be less practical in real driving conditions that it can not provide prompt responses to alert drivers.

3.1.2 Critical Driving Event at Intersections

In this work, we present SafeCam, a smartphone-based system that detects and identifies intersection-related drivers' unsafe behaviors [18]. Our goal is very simple: to prevent crashes/accidents that may change lives forever. SafeCam focuses on most commonly occurring critical driving events at intersections including the stop signs/red light infractions, unsafe turns, hard acceleration/braking and speeding, as illustrated below.

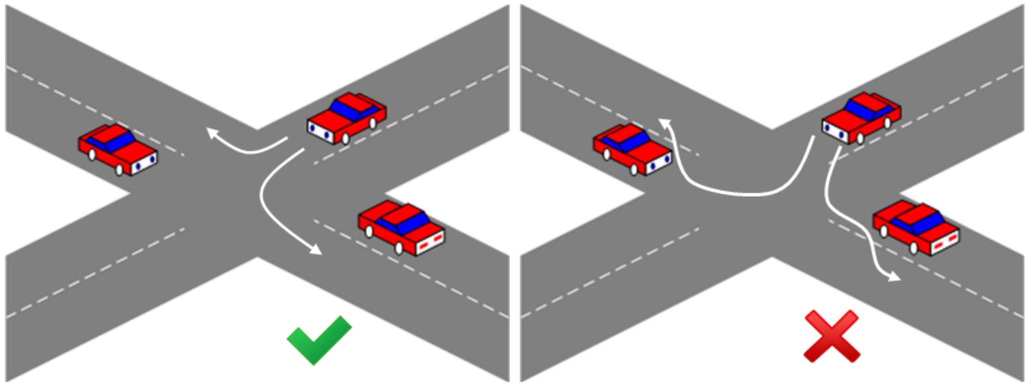


Figure 3.1 A sample safe/unsafe driving event scenes for right and left turns. The unsafe turns (in right figure) may result in angle-impact or sideswipe crashes to the cars on both sides

- ***Stop at Stop Signs***. Running stop signs or failing to fully stop is dangerous to drivers, passengers and pedestrians. It will highly increase the risk of traffic collisions. According to the study [72], over 700,000 crashes are reported annually at stop signs which result in a large number of injuries or disabilities. In our design, SafeCam should be able to monitor and determine whether the driver brakes and stop the car properly when he is approaching a stop sign .

- ***Stop at Traffic Lights***. Drivers should prepare to stop the vehicle when the traffic light is becoming red. However, we can always see that a vehicle speeding-up to run a yellow light, and sometimes even a red light. Running yellow/red lights can be extremely dangerous. In a national telephone survey by the AAA Foundation for Traffic Safety [138], 35 percent of drivers admit that they had driven through a red light in the past 30 days, though they believed it is a serious threat to their personal safety. Alerts should be sent to drivers when SafeCam detects such behaviors.

- ***Unsafe Turns***. When making a turn at intersections, a driver often fails to follow his/her own lane or enters a wrong lane after leaving the intersection (as shown in Fig. 3.1), as well as have a high turning speed, which often results in car to car accidents such as angle-impact and sideswipe crashes. The system should track vehicle turning movements and provide real-time alerts/feedback if a driver exceeds the safe turning speed or a lane drifting/crossing problem occurs during the turn.

- ***Hard Deceleration/Braking***. Hard deceleration (braking) can be an indicator of aggressive/unsafe driving. As the driver may has been involved in an accident or increase the risk of nose-to-tail crashes. In addition, frequent hard acceleration and braking also consume extra fuel and emit more harmful gas to the air. Thus, shape the green driving habit is good for people on road and the planet.

- ***Vehicle Speed***. Speeding is one of the leading cause of car accidents and also a potential safety challenge to pedestrians at intersections. According to the study [139], a pedestrian hit by car at 50 km/h has an 80% chance of being killed, while a pedestrian hit by car at 30 km/h has a 90% chance of surviving. Drivers have responsiblities to maintain a safe driving speed (including turning speed), which would help them to have more time to react and reduce the severity of injuries when crashes occur.

The rest of this chapter is organized as follows. We first discuss the system design considerations and implementation challenges in Section 3.2, and then Section 3.3 presents the basic features of driver behavior detection model including vehicle dynamic sensing, traffic control information recognition (vision-based), as well as driving event identification. The real-road driving experiments and the evaluation results are shown in Section 3.4.

3.2 Design Consideration

SafeCam can detect and record critical driving events at intersections including speeding, aggressive acceleration/braking, stop signs/red light infractions, unsafe turns and lane changing. The system is designed to provide both real-time alerts and periodical feedback to drivers on their bad/unsafe driving habits and associated potential risks. In addition, the smartphone is mounted on the vehicle's windshield with rear-facing camera(s) toward the road ahead, as illustrated in Fig. 3.2. We assume that the smartphone can be plugged into the vehicle power outlet. Thus the battery running time of SafeCam is not considered in this work.

In order to implement the proposed system, we address the system design considerations in practise as follows:

Figure 3.2 In-Vehicle System Setup.

- ***Robustness to Real-Road Conditions***. The vision-based detection (e.g., red light and stop sign) can be easily affected by real-road light conditions such as vehicle vibration, strong sunshine and cloudy weather. The system may also fail to recognize the target due to color fading or damaged surface, while falsely detect a number of arbitrary objects on road have similar color/shape features as traffic signals or stop signs (e.g. vehicle taillights, people wearing red jackets). An efficient computer vision based model is needed to meet the variable challenging conditions.

- ***Image Quality and Computational Feasibility***. Unlike some high-end digital video recording devices, frames captured by smartphone cameras have relative lower resolution, which may become worse due to vibration and lighting condition. On the other hand, smartphones have limited processing resources, especially for image processing and vision-based algorithms. Traditional computer vision techniques may not be suitable for mobile sensing platforms in real-road scenarios. The driving event detection is time sensitive, it is desirable to have a lightweight system design with a trade-off between the detection rate and processing delay.

- ***Driving Event Identification***. In real driving scenarios, SafeCam should be able to identify different driving events based on the information from vehicle dynamic sensing and vision based detection. A well designed scheme is needed to determine whether a driving behavior is dangerous. For example, when a vehicle is passing the intersection, the traffic light is yellow and it is unsafe to make a sudden stop (the vehicle is very close to the intersection). But the light will become red very soon, if the driver do not make a stop it is very likely to be recorded as dangerous driving. SafeCam should be able to understand such cases by checking the speed, accelerations and location of the vehicle.

3.3 System Design

3.3.1 System Overview

The key components of SafeCam are designed as driving dynamic sensing, vision-based driving event detection and offline driver behavior analysis, as illustrated in Fig. 3.3.

Driving Dynamic Sensing. We use smartphone embedded sensors including accelerometer, gyroscope and GPS to track and monitor the vehicle acceleration, rotation rate (angular speed), running speed and location information. The sensing data are used in both the driving event detection and the offline driver behavior analysis.

Vision-Based Driving Event Detection. SafeCam recognizes driving events by analyzing the driving dynamic data upon the online vision-based detection results. In order to improve the system efficiency, we first leverage a acceleration-based filter to remove poor quality frames caused by vehicle vibrations. Secondly, we adopt the window selection and a subsampling method to reduce the frame processing time. In order to be robust to outdoor light variations, two weather conditions - sunny and cloudy are considered in the vision-based detection. A location-based method is used to trigger the red light detection that avoids false positives on road. Finally, we extract the shape features of candidate regions and determine if the detected object is a stop sign or a red light. In addition, the lane marker detection using Hough-line transformation [140] is also provided to check if a driver follows the proper lane when the vehicle crosses the intersection.

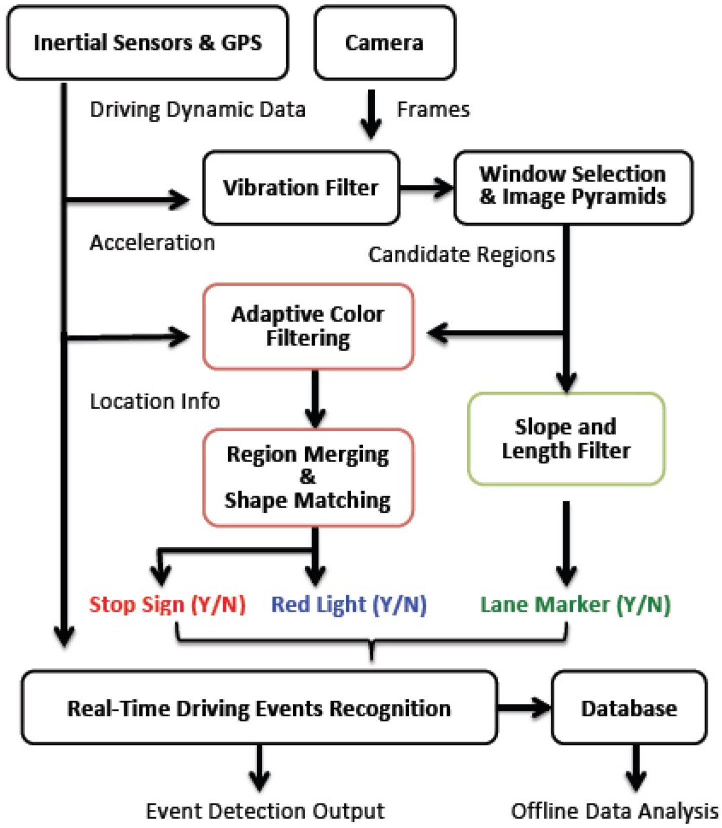


Figure 3.3 System Overview.

Offline Driver Behavior Analysis. All the sensing data, vision-based detection results and driving events records are stored using text format in the smartphone as the user driving historical data for further offline analysis. We examine the intersection-related driving behaviors including the habits of making turns, driving speed, braking time at stop signs and traffic lights. The size of one hour driving historical file is less than 400 KB - one day (24 hours) is less than 10 MB, thus the smartphone storage is capable of long term monitoring use.

3.3.2 Driving Dynamic Sensing

During the road trip, SafeCam keeps tracking the vehicle speed, acceleration, angular speed (g_x), bearing (the vehicle moving direction) and the location data. The measurement and calculation are conducted in a standard 3-axis coordinate system [141] as illustrated in Fig. 3.4. The smartphone is mounted on the windshield of the vehicle, and the rear camera is kept facing the road ahead without obstruction. It should be noted that we consider the smartphone and vehicle share the same coordinate system. In cases where this does not hold, the coordinates alignment can be done with existing work [84, 118] .

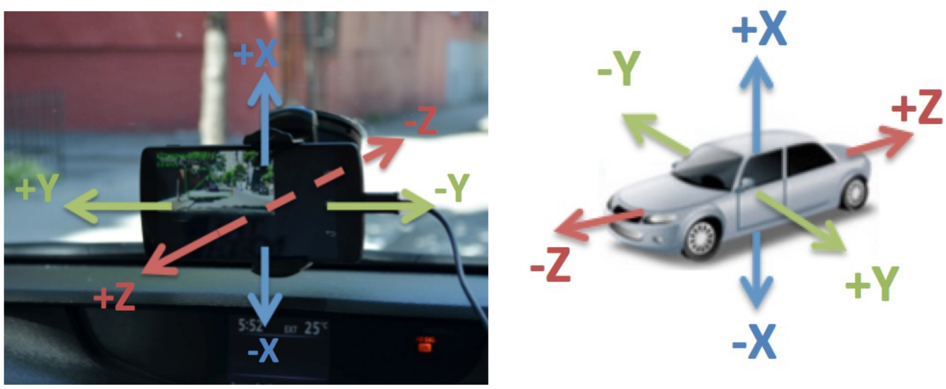


Figure 3.4 Coordinate System.

Driving Speed Estimation

In SafeCam, we obtain the vehicle speed using the geographic location class provided by Google location API. However, this API cannot reflect the frequent changes of the vehicle speed during turns. It is reasonable to assume that the vehicle turn follows a perfect circle [118], the turning speed υ can be estimated by integrating the centripetal acceleration and angular speed [84]:

$$\upsilon = \frac{a}{\omega}, \tag{3.1}$$

where υ is the turning speed of the vehicle, a is the centripetal acceleration, ω is the vehicle angular speed of the turn.

Acceleration and Turn Detection

SafeCam leverages accelerometer values $A = \{a_x, a_y, a_z\}$ in m/s^2 and gyroscope values $G = \{g_x, g_y, g_z\}$ in rad/s to sense vehicle movements. When a vehicle is moving along a straight line, the Z-axis reading of accelerometer reflects the moving accelerations, the a_z is positive when the vehicle brakes, and vice versa. The gyroscope data is the indication of rotation movements. The angular speed g_x - the X-axis reading of the gyroscope reflects the turning speed and turning directions of a vehicle. It generates positive reading when the vehicle is turning left, and a negative reading during a right turn. According to Wang's study [118], we set 0.5 rad/s as the threshold in turn detection.

Sensor Data Adjustment

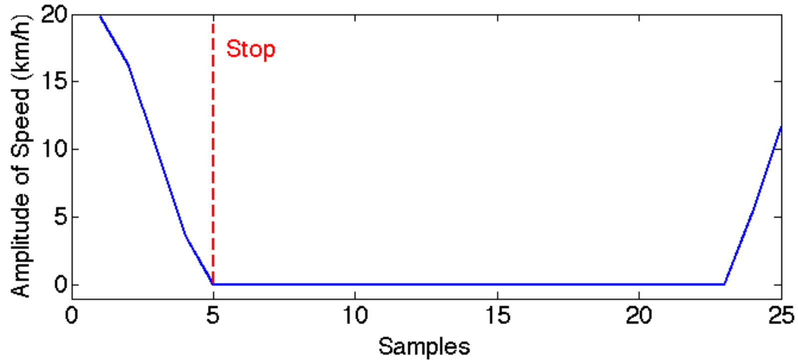
In addition, the value of smartphone sensors (accelerometer and gyroscope) may have a constant value different from zero even there is no movements [84,118]. In order to eliminate the effect of such a bias, we design an stop-start method to adjust the acceleration and angular speed (As shown in Fig. 3.4).

1. During a road trip, a vehicle may stop multiple times (e.g. red lights, stop signs). Every time SafeCam detects a stop (when the speed reading is zero), the stop-start measurement is triggered.

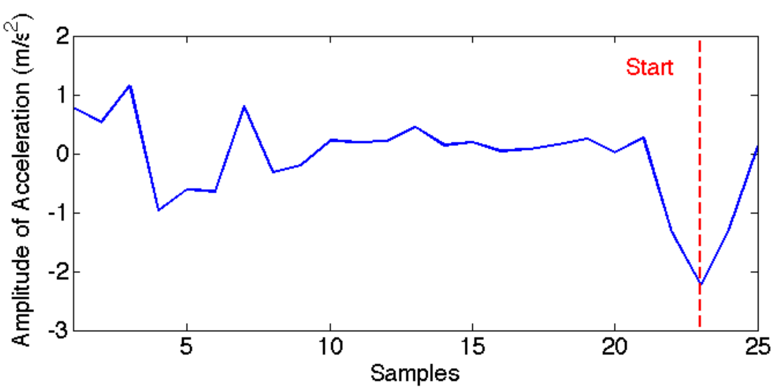
2. The system calculates and records the mean value of the acceleration/gyroscope readings during this time period.

3. The system leverages Z-axis acceleration reading to detect if the vehicle starts to move again. Because the acceleration reflects the movements earlier than the speed readings by using GPS. In addition, the value of Z-axis acceleration when a vehicle starts is much higher than the system bias, the threshold in vehicle-start detection is -2m/s^2. Thus, we do not need to worry about the false detection. When the vehicle move is detected, the system stops the measurement and subtracts the recorded mean value from all the acceleration/gyroscope readings to remove the constant bias.

The loop continues the stop-start measurement at next stop period. The system keeps calculating the new mean value till the end of the trip.



(a) STOP detection



(b) START detection

Figure 3.5 An Example of Stop-Start Method. (a) The system detects STOP - the vehicle speed is 0. (b) The system detects START - the acceleration exceeds the threshold.

3.3.3 Vision-based Driving Event Detection

By leveraging the smartphone sensing data and vision-based algorithms, SafeCam is able to detect critical driving events at intersections. The system examines the vehicle speed and acceleration (Z-axis readings) within a sliding window of 5 seconds (the distance a driver can react) before and after a stop sign/red light is detected. For stop sign events, the system can record three types of events include complete stop, slowly passing (speed under 10 km/h, fail to fully stop) and normal speed running (speed over 10 km/h), the braking time is also recorded for offline analysis. For red light events, as we discussed in Section 3.2, SafeCam checks if the drivers slow down and take a complete stop when they are facing a red light.

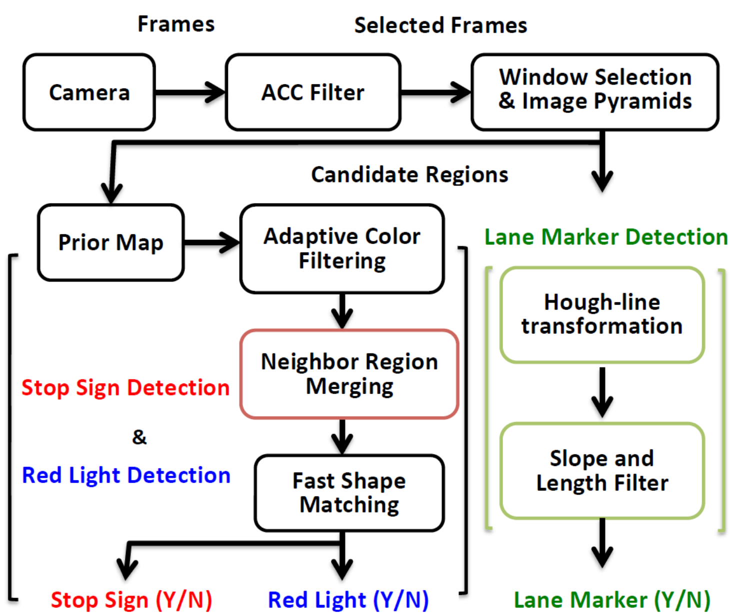


Figure 3.6 Vision-based Driving Event Detection in SafeCam.

Vibration Filter

In smartphones, the video frame capture rate (e.g. 30 fps) is much higher than the processing rate (see section 3.3.3). On the other hand, low quality frames (e.g. blurry or out of focus) often lead to large detection errors and have strong effects on the system performance. Therefore, we prefer to feed the frames with good quality to the OpenCV processor. However, evaluating frame quality requires both objective mathematical models and subjective quality assessment - sometimes need a trained expert to judge it, which is unfeasible to the real-time recognition system.

Since camera vibration is a major cause of poor frame quality [142]. In SafeCam, we filter out the frames (most of which have low image quality) when the vehicle is shaking or vibrating. The vehicle vibrations are mainly caused by speed bumps, potholes, and uneven road surface , which can be inferred by accelerometer readings [54, 143]. Our system leverages the X-axis (gravity direction) reading of accelerometer to detect vibration. According to [54], we detect x-peak with a threshold of 1.45g and the worst case of video frame capture rate is 5 Hz (discuss later).

Detection Window and Image Pyramids

Traffic signals often appear only in the specific part of a captured video frame [99], as well as stop signs and lane markings. Based on our observation, the lower half of the frame only captures the car hood. Therefore, we select a set of detection windows instead of processing the whole frame to reduce the computation costs for frame processing, as shown in Fig. 3.7. More importantly, by removing a large portion of a captured frame that has nothing but noise. The detection rate of vision-based algorithms are significantly improved.

To achieve a higher processing frequency, we also deploy a Gaussian pyramid [144] method which converts the image to a smaller size by downsampling (Remove every even-numbered row and column of the image). The resulting image will be exactly one-quarter the area of the original frame. Thus the system processing time is double halved. As shown in Table 3.1, our window selection (WS) plus Gaussian pyramids method achieves a 200 ms frame processing time (worst case) which is much faster than [99] - 2 seconds.

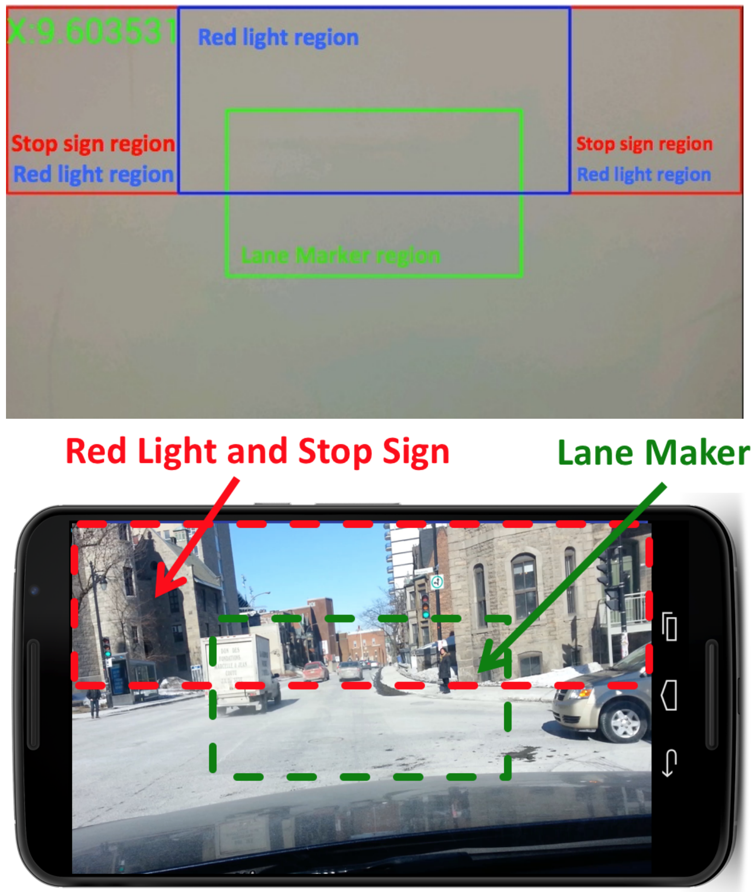


Figure 3.7 Detection Windows. the red windows are for stop signs detection, the red light detection covers both red and blue windows, and the green window is for lane marker detection.

Location Triggered Traffic Signal Detection

In red lights and stop signs detections, the system accuracy suffers from the interference of other red color objects. It is likely that the taillights of vehicles, persons in red jacket and colorful billboards are often falsely recognized as red lights or stop signs. Most of these errors occur out of the intersection areas, which inspires us to develop a location triggered traffic light detection (as shown in Fig. 3.8). The basic idea of our algorithm is to start the red-light detection only when the vehicle is approaching and close to the intersection. If the vehicle is leaving or far away from the intersection with traffic lights, no red light would be detected by the system. Based on this strategy, the interferences of red-objects can be largely reduced. Moreover, we significantly decrease the computation in vain when there is no traffic light ahead - the system will not scan the red light detection window (nearly half of the detection area).

Table 3.1 Image Processing Latency.

Methods	W/O GP and W/O WS	W/O GP and W/ WS	W/ GP and W/O WS	W/ GP and W/ WS	SignalGuru
Processing Time (ms/frame)	1500 - 2500	1100 - 1500	600 - 900	150 - 200	2000

In the implementation, we build a prior map in SafeCam by applying data from OpenStreetMap [145]. The prior map contains the location information of traffic signals (latitude and longitude) which can predict the upcoming intersections. By measuring the distance between the current vehicle and the approaching traffic lights based on Haversine formula [146] (the stop sign location information is not available from online data source, and will be discussed later in Chapter 5). The system enables the red light detection only if the the vehicle is within 30 meters to the traffic light. We also observe that traffic lights and stop signs do not coexist at the same intersection. Therefore, when the red light detection is on, the system will not enable the stop sign detection.

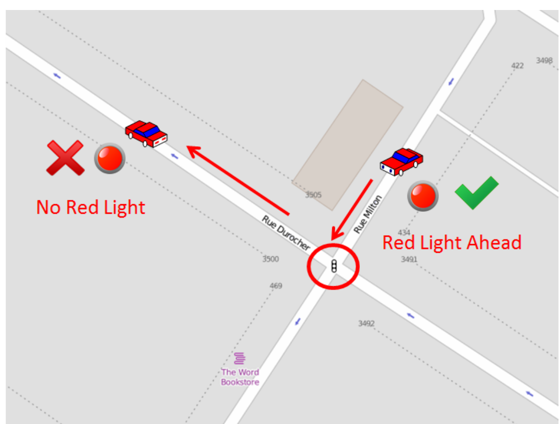


Figure 3.8 An example of Location Triggered Traffic Signal Detection.

In addition, we use the bearing information to determine the vehicle moving direction. The bearing is defined as the angle in degrees (0 - 360) East of true North when traveling along the shortest path between the current location (the vehicle) to the target location (the traffic light) [141]. Once the a traffic light is passed, the system updates the next approaching traffic light location. By actively switching the detection of red lights and stop signs rather than executing both of them, the SafeCam system saves considerable computing resources and the false positive rate of the traffic signal detection dramatically decreased.

Weather-Adaptive Color Filtering

We use the HSV (Hue, Saturation, Value) color space instead of RGB to extract the candidate regions for stop signs and red lights detections. Compare to the RGB color space, the HSV color space corresponds better to the color components segmentation and be more robustness to light condition changes [147, 148]. The color properties of stop signs under different weather conditions varies significantly (purple color in cloudy days, orange color in sunny days, etc.). However, a wider color filtering range may cause considerable image noise and affect the system performance. In order to minimize the effects of outdoor light variations efficiently, SafeCam deploys a weather-adaptive range selection to segment possible stop sign regions. We classify input frames into different weather conditions according to the mean value of the frame saturation. The S value from 7 to 25 is classified as the cloudy (low saturation) condition and the S value from 26 to 100 is classified as the sunny (medium to high saturation) condition. If the mean value is under 7, the frame is filtered out due to its poor intensity.

Based on our test, the HSV color range of stop signs in sunny conditions is: Hue (0-15) and (310-360), Saturation (41-100) and Value (20-100). And the HSV color range in cloudy conditions is : Hue (0-15) and (310-360), Saturation (15-40) and Value (20-80). The weather-adaptive color filtering significantly improved system performance, an example of the stop sign detection is illustrated in the Fig. 3.9.

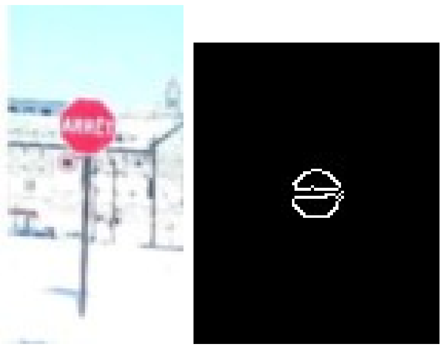
Figure 3.9 An Example of Adaptive Color Filtering. The stop sign detection failed without weather-adaptive color range (left). With the aid of adaptive range selection, SafeCam is able to detect stop signs on both sides of the road (right).

In addition, the color range of red lights is more complex under different weather conditions [99]. It may become brighter in cloudy days, and partly become yellow under shadows. Unlike the stop sign, the S and V values of red light are stable. While the H value of the red light has two conditions - pure red color and yellow surrounded by red. Thus, the HSV thresholds to red light detection has a wide range of Hue, and high value for both S and V : Hue (0-15), (17-65)and (330-360), Saturation (60-100) and Value (60-100).

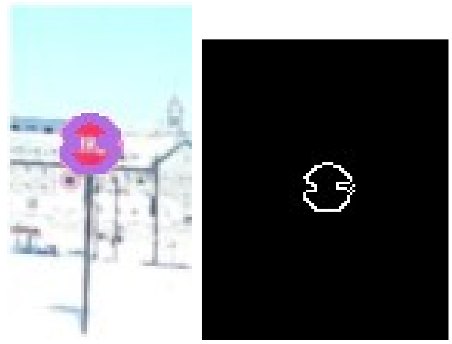
Neighbor-Frame Region Merging

In the road test, we observed that the stop sign detection is often affected by its white content "STOP" or "ARR$\hat{E}$T" [1], which divides the red region into two separate parts, as illustrated in Figure 3.10(a). To address this issue, we employ a region merging method, which takes the advantage of correlation between neighboring frames. Since the normal frame capturing rate is 5 Hz, we consider that two neighboring frames - $frame_{Current}$ and $frame_{Next}$ share the same image coordinates and have similar features.

[1] ARR$\hat{E}$T is french for Stop and used on stop signs in Quebec.



(a) The contour detection before region merging.



(b) The contour detection after region merging.

Figure 3.10 Stop Sign Contour Merging. (a) Before region merging - the contours are divided into two parts. (b) After region merging - the contours are connected together.

The candidate regions are classified into groups based on the centroid distance between each other. As shown in Equation 3.2, the centroid of contours is $(\bar{x}_c, \bar{y}_c)$, and the centroid distance $D_{c_{ij}}$ between contour i and j is measured using Euclidean distance. If $D_{c_{ij}}$ is under 30-pixel, i and j are classified as nearby contours.

$$D_{c_{ij}} = \sqrt{(\bar{x}_{c_i} - \bar{x}_{c_j})^2 + (\bar{y}_{c_i} - \bar{y}_{c_j})^2}. \tag{3.2}$$

Finally, in the processing of $frame_{Next}$, we merge the nearby regions together based on the classification results in $frame_{Current}$. The method connects the small separated parts into a new, larger region, which can be detected by the system, as illustrated in Figure 3.10(b).

Fast Shape Matching

In SafeCam, we leverage the shape feature to determine if the candidate regions are approximate to a stop sign or a red light. Two standard templates - a red octagon for the stop sign and a red circle for the red light are used in the shape matching. The similarity between the detected contour and template is measured by using an OpenCV function as,

$$I(C,T) = \left| sv_C - sv_T \right|, \tag{3.3}$$

where $I(C,T)$ is the score that measures the differences between candidate objects and the template, the lower $I(C,T)$ indicates the better matching. sv_C and sv_T are vectors that represent the shape features of the objects. If a sufficient matching is found ($I(C,T)$ is less than 0.02), we consider the object as a stop sign. What is more, the contour shape of a red light is not a perfect circle due to the light scattering and refraction. Thus we have a larger threshold of $I(C,T)$ which is up to 0.1 in red light shape matching.

Lane Drifting Detection

Although the lane maker detection is widely used in many driving safety applications [32], in this paper, we mainly focus on intersection-related lane drifting issues. The lane drifting detection is deployed in SafeCam to check if the driver follows the prescribed lanes when the vehicle enters or leaves a intersection as illustrated in Fig. 3.1. We first uses the canny edge detector on lane marker region and then leverages a Probabilistic Hough-line transformation [32, 149]. The Probabilistic Hough-line transformation identifies line segments based on the edge-image and returns extremes of the detected lines (x_0, y_0, x_1, y_1). Base the detection result, we compare the slope and length for each line vector to select lane markers, a lane marker should have a length over 30 pixels and the slope range should be from 0.6 to 10. During the turns, if the midpoint of the lane marker crosses the center-line (vertical) of the lane-marker detection window (the green rectangle window shown in Fig. 3.7), a lane drifting event will be recorded by the system.

3.4 Evaluation

In this section, we evaluate SafeCam in real-road driving environments. Specifically, we first describe the experiment setup and datasets, then present the results of online vision-based detection under different ambient lighting conditions. Moreover, we analyze the driver behaviors based on the sensing data from the experiments.

3.4.1 Experiment Setup and Datasets

We implemented SafeCam on a Google Nexus 5 Android smartphone (Manufactured by LG) which is equipped with a Quad-core 2.3 GHz Krait 400 CPU , 2G RAM and 8 MP rear-facing camera. Another smartphone (Nexus S) was also installed to constantly capture frames using the rear camera. We manually labeled ground-truth driving events by replaying recorded videos. SafeCam sensed the driving dynamic data including vehicle speed, acceleration, angular speed and location information (bearing, latitude and longitude). In addition, the raw data and vision-based detection results were stored on the phone for offline analysis.

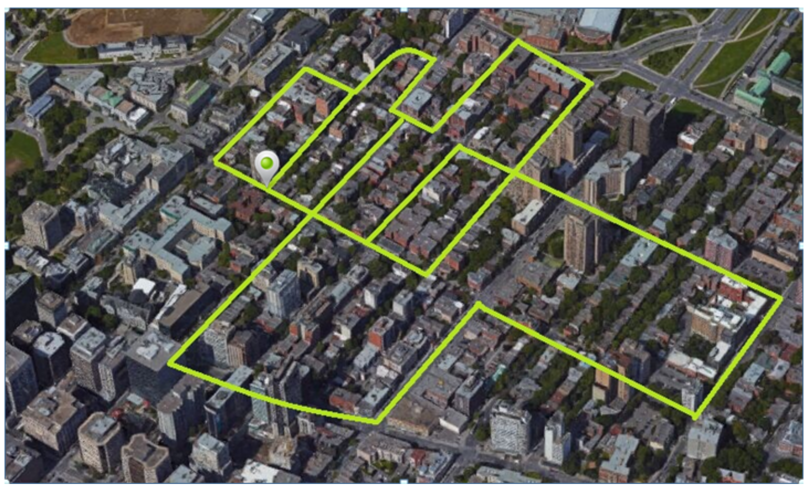


Figure 3.11 Real Driving Routes.

We selected a driving route (3.5 km) in Montreal downtown area as shown in Fig. 4.10. There are 9 stop signs and 14 traffic lights per route. In our experiments, we recruited 15 participants - 5 female drivers and 10 male drivers from age 25 to 40 (driving experience from 2 years to 15 years). There are 6 different vehicles involved in the study including Audi Q5, Toyota Venza, Ford Escape, Toyota RAV4 and Honda Civic (2 different models). Participants were suggested to drive their own vehicles. Each participant's record contains 40-minute of driving. The driving traces were collected under different weather conditions (e.g. cloudy, sunny) on different days.

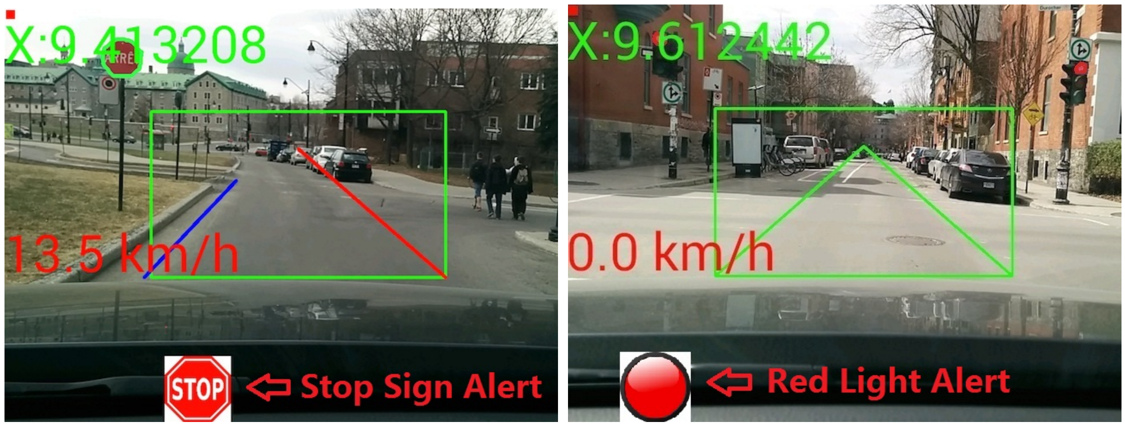


Figure 3.12 Examples of the Online Vision-based Detection in Real-Road Driving. The stop sign detection (left), the red light detection (right) and the lane marker detection (both).

3.4.2 Vision-Based Driving Event Detection

In real-road experiments, driving event detections mainly rely on the performance of the traffic control device perception. We examined the ability of SafeCam in detecting stop signs, red lights and lane markers and related driving events, as illustrated in Fig. 3.12. To evaluate the system performance, we define the metrics including true positive (number of driving events that are correctly identified), false positive (number of unrelated objects are classified as target events), precision and recall. Table 3.2 provides the detailed results across all scenarios.

As illustrated in Table 3.2, the overall precision and recall for stop sign detection are 84% and 81%, respectively. The detection errors are mainly occurred in several challenging light conditions such as rainy, sunset, nightfall, etc. During the road trip, 46 out of 53 running stop sign events were detected. The majority of false positive cases (5 events) are due to road-side red color objects (e.g., vehicles, buildings, and other road signs), detailed analysis are provided in section 5.2.

Table 3.2 Vision-Based Detection.

Conditions	# of TPs	# of FPs	# of Ground Truth	PR	Recall
Stop Sign Detection	109	21	135	0.84	0.81
Red Light Detection	58	15	70	0.8	0.83
Stop Sign Driving Event Detection	46	5	54	0.85	0.87
Red Light Driving Event Detection	4	1	5	0.80	0.80
Lane Drifting Detection	43	11	53	0.80	0.81

The precision and recall for red light detection are 80% and 83%, respectively. Traffic lights have a fixed luminous intensity, which can keep good saturation and lightness in cloudy conditions. However, we find that red lights are often not captured well under sunny conditions with their bulbs appearing yellow color. The cause of these particular cases is that small red targets (LED traffic signals) can appear yellow when viewed through small amounts of defocus under bright illumination [150], which limits the detection accuracy of our system. A study on yellow light detection is required in the future work to improve the system accuracy.

Few drivers were found to run a red light, as they tended to drive cautiously when being monitored by the system. However, several drivers in experiments failed to do a safe stop when they were facing a yellow light. The traffic light changed to red immediately after the vehicle entered the intersection. According to the system design, the events are recognized as running red light. SafeCam is capable of detecting such potential dangerous cases [151] (4 out of 5 events were detected in the experiments). In addition, location-based red light prediction well reduced the false positive rate. One special case is that a driver followed a truck which has a high-position red taillight when passed an intersection. The system wrongly record it as a red light and resulted in a lower precision.

The results of lane drifting event detection have been shown in Table 3.2. The detection recall (81%) of the system is mainly affected by the color fading and damage of lane markers, where the road conditions are not good. Furthermore, we also analyze the cause of the false positive cases. We find that some roads have turn lanes for vehicles. The driver drifts into the turn lane first and then made a turn at intersections without any stop when the traffic light is green. The system may confuse these two steps for a turning behavior and record it as a lane drifting event. We may further analyze the vehicle acceleration patterns to identify such conditions avoiding false detections.

3.4.3 Driving Behavior Analysis

In this section, we use participants' data to analyze unsafe driving behaviors at intersections including unsafe turns (lane drifting and turning speed), braking (hard and normal) and average braking time at intersections. For privacy concern, we represent participants using user ID from 1 -15, among these user IDs, No. 1 - No. 5 are female participants.

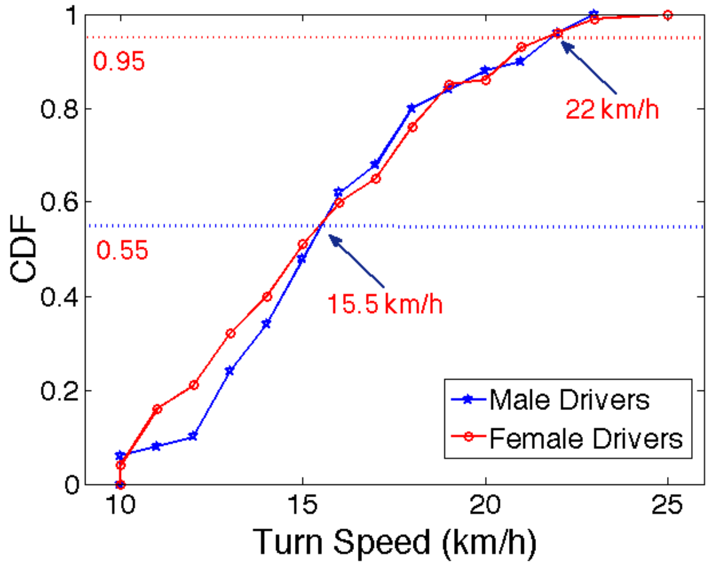


Figure 3.13 CDF of the Turning Speed at Intersections.

Through the experiments, the data shows that drivers often pay less attention to lane drifting problem at intersections. 11 out of 15 participants at least failed once to stay in the proper lane during the turn or enter a wrong lane when left the intersection. Moreover, we analyzed the turning speed of participants at intersections and plot the cumulative distribution function (CDF) in Fig. 3.13. According to the experiments data, the turning speed of the vehicles are all higher than 10 km/h. The maximum value of the turning speed is 25 km/h and the mean value is 15.85 km/h. In Fig. 3.13, for both male and female drivers, 95% of the turning speed is under 22 km/h and nearly 55% of the turning speed is under 15.5 km/h. Thus, we divided the turning speed into three groups: 10 - 15.5 km/h as low-speed group, 15.5 - 22 km/h as mid-speed group and over 22 km/h as high-speed group. Drivers in the high-speed group (5 out of 15 participants have been recorded) will get the feedback that reminds them to pay more attention when they are making turns.

Fig. 3.14 shows that through our study with over 250 braking events collected from 15 drivers' real-road driving, nearly 80% (0.1 to 0.9 in CDF) of the maximum reading of deceleration during braking is from 1.5 to $3m/s^2$. We thus choosed 1.5 - 3 m/s^2 as the normal acceleration range and selected $3m/s^2$ as the threshold in the hard braking detection. In the real-road driving experiments, 8 out of 15 participants made hard braking.

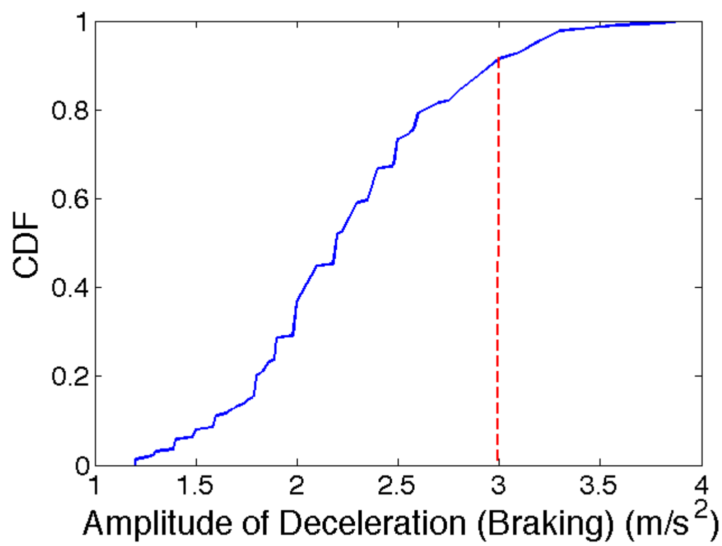


Figure 3.14 CDF of the Deceleration (Braking) at Intersections.

During the experiments, we observed that there existed certain differences between the behaviors of male and female drivers. In order to validate this observation, we further conducted in-depth analysis on their traces. As illustrated in Table 3.2, running stop sign is becoming a common problem for drivers. Fig. 3.15 shows that more than 95% of these cases are slowly passing (fail to fully stop) with a speed from 3 to 10 km/h. The female drivers were more carefully than male drivers when they were approaching stop signs - only 1.8 events per person are detected. Especially, the user No. 5 did not run any stop signs at all. Meanwhile, the male drivers contributed 37 out of 46 events with an average number close to 4.

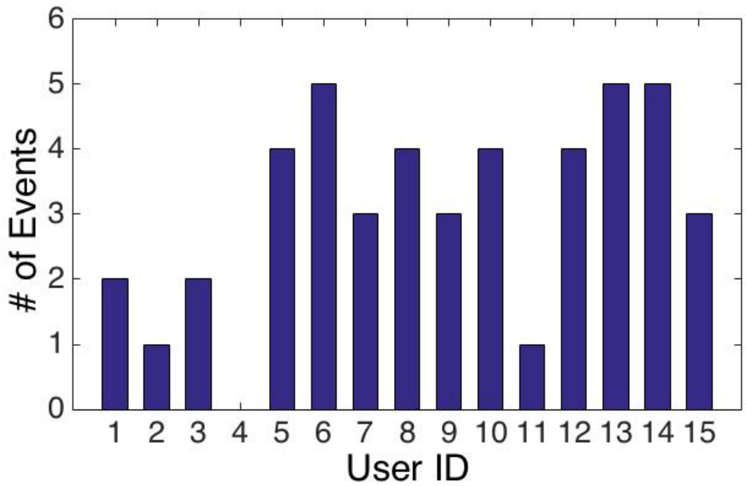


Figure 3.15 User Behaviors at Stop Signs. Stop Sign Running Events

We analyzed the braking time of each user when they approached the intersection, as illustrated in Fig. 3.16. Based on the sensing data, we found that participants took longer braking time when they approached a stop sign than approached a traffic light. The average braking time at stop signs is 8 seconds for male and 10.5 seconds for female, and the average braking time at red light is 6.5 seconds for male and 8.5 seconds for female. It is because that the traffic light has a higher uncertainty compare to the stop signs - the traffic states changes more frequently while stop signs do not.

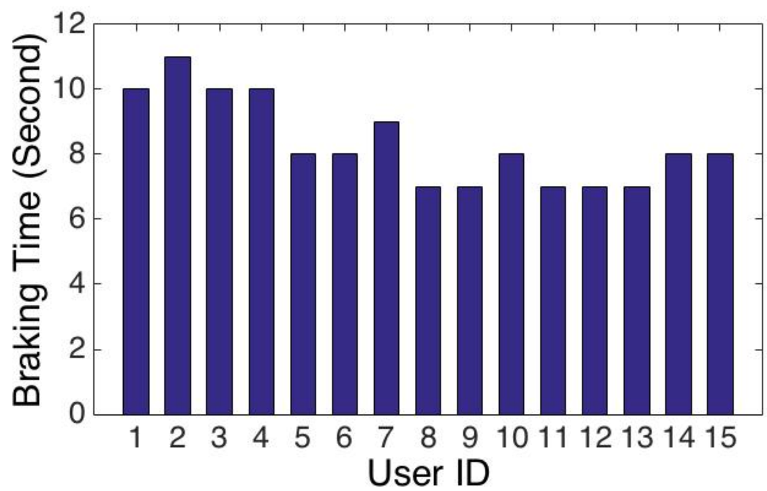


Figure 3.16 User Behaviors at Intersections. Braking Time at Stop Signs.

3.5 Limitations

3.5.1 Driver View Field Analysis

To fulfill the functionalities of SafeCam, it is also important to know the driver's view field to investigate if the driver is aware of the crossing pedestrians, the road sign [18], the approaching traffic, etc. Such systems are useful to drivers and could avoid fatal road accidents involve inattention driving. In You's work [32], authors develop the eye state (open or close) detection algorithm to check if the driver is tired or distracted. However, a driver may open the eye and facing the road but not focus on the object ahead. Therefore, by combining eye gaze and hand motion information, the system could provide a comprehensive study of the distracted driving behaviors, as well as drowsy driving. We would also consider analyzing driver eye gaze direction and driving behaviors in various road conditions.

Chapter 4

SafeDrive: Detecting Distracted Driving Behaviors Using Wrist-Worn Devices

This chapter is reproduced from the following published article, with the permission from ACM:
Landu Jiang, Xinye Lin, Xue Liu, Chongguang Bi, and Guoliang Xing. 2018. "SafeDrive: Detecting Distracted Driving Behaviors Using Wrist-Worn Devices", Proc. ACM Interact. Mob. Wearable Ubiquitous Technol (IMWUT - UbiComp Journal). 1, 4, Article 144, January 2018.

4.1 Background and Motivation

Distracting activities while driving are common and can cause fatal accidents and serious injuries, which have become a major threat to the traffic safety [125, 152, 153]. Most of us have at least one or more distracted events during everyday driving [154, 155] such as interacting with the infotainment devices [156] like music, GPS, radio, and the use of mobile devices is also prevalence recently [118,157]. Unfortunately, we always fail to realize our bad behaviors and many drivers may view distracted driving as a minor offense even though it will affect the control of the vehicle and result in driving errors. In addition, there is particular concern about the potential detrimental effects of distraction among adolescent/young drivers. Because they are relative lack of driving experience while more likely to use portable and in-vehicle electronic devices [158]. Thus it is desirable to apply strategies to minimize driving distractions that help drivers to raise awareness of the risk conferred by different distracting activities and the circumstances.

Driver distraction can be defined as any activity that diverts a driver's attention away from the task of driving [159]. We can commonly split in-vehicle driving tasks into two classes (some approaches use three classes): primary tasks and secondary tasks. The primary driving task comprises all activities that are required to maneuver the vehicle such as the tasks regarding lateral and longitudinal control of the vehicle as well as "maintaining alertness to traffic and other potential hazards" [160]. The secondary tasks demand vary in complexity compare to primary tasks, which involve driving related activities or non-related activities to driving [161,162]. We define driving related activities that are related to safely control the vehicle (i.e., the traditional primary driving task) or to increase driving safety or performance (e.g., adjusting a mirror, navigation). While non-related activities are other tasks/activities such as operating infotainment systems, using smartphones/texting, eating and drinking [36, 163]. Results indicate that the interaction with secondary tasks have the detrimental effects on driving performance such as significantly shorter headways, increased braking pressure, and significant compensatory speed reductions [156]. In this study, we address driver distractions associated with unsafe secondary tasks (both driving related and non-related activities) to promote road safety.

Though the sources of distraction may take various forms, we can examine distractions in terms of three basic categories [161,164]: 1. Visual, which takes your eyes off the road, 2. Manual, which takes your hands off the steering wheel, and 3. Cognitive, which takes your mind off the road. Distracting activities that drivers engage in always involve more than one of these components (e.g., visually searching for an item at passenger seat). A number of vision-based driving safety services have been proposed to prevent driving distractions (visual) by tracking the driver eye state and face/head directions [30, 32, 111]. However, such systems are not practical if a driver "looked but did not see" [165] (e.g., situations where the driver may use less eye contact, while their hands and minds are already off the road, or not fully attentive to the surrounds). It is hard to detect distracted behaviors if drivers want to keep looking at the traffic ahead and just take a very quick glance (e.g., less than 1 second) on other tasks (e.g., tuning music, opening sunroof, etc.). On the other hand, distracted driving events such as texting, eating/drinking or reaching items often require a combination of visual, manual, and cognitive attention from the driver. We find that manual behaviors are involved in most of driver distracting activities, and thus can be used as major hints to infer unsafe driving events.

4.2 Design Considerations

4.2.1 In-vehicle Driver Behavior Monitoring

In this project, we aim to build a driving safety system that detects distracted driving events by tracking driver hand movements. Several systems have been provided in the market to determine whether a driver's hands are on or off the steering wheel [1, 34]. Our prior work also addressed this problem by exploiting wrist wearable sensing to track driver hand motion and forearm postures [2] (as shown in Fig 4.1). We believe that the in-vehicle driver behavior recognition has two main advantages:

1. Understanding driving in-vehicle behavior is the key to reduce the possibility of driver distractions and car accidents. Existing solutions (eye/face tracking, hands on/off the steering wheel) usually use a three-second scheme to trigger the alarm [32]. It allows drivers to carry out some secondary/tertiary tasks to improve driving performance such as heating the windows, control the system, etc. However, if the driver is performing a dangerous behavior, the system becomes less practical if it still waits the same period of time. For example, if a driver is eating a sandwich, he/she is still holding the food when the alarm is beeping. It will take extra time for driver to bring his attention back to the road, while an accident may have already approached. Identifying the driver behavior may help the system detect dangerous in-vehicle activities, thus, can alert driver properly for the dangerous driving event and use a normal threshold for secondary/tertiary driving tasks.

2. In addition to the hands on/off systems, driving behavior recognition can provide a more detailed feedback to drivers. Our purpose is to educate drivers about the dangers of driving distractions. A good driving safety system should not only alert the drivers (e.g., merely block smartphone use) but also help them to shape good driving habits.

Towards this goal, we leverage the off-the-shelf wrist-worn device (smartwatch) to track and analyze driver hand (right) movements. Recently, the emerging ecosystem of mobile and wearable sensing platforms is becoming increasingly successful. Wrist-worn devices have been exploited for human activity recognition in many areas [135, 166–168]. These devices, such as smartwatches and activity trackers (other wearable products), are equipped with inertial sensors (e.g., accelerometer and gyroscope) that can capture the dynamics from user's hand movements continuously. We foresee that the functionality and convenience of wrist-worn devices would offer us a great opportunity for fine-grained hand motion tracking and detecting in-vehicle distracting events. Moreover, the smartphone has already been widely used for activity recognition, which is capable of running heavy tasks (e.g., machine learning algorithms) and has enough storage space for the activity sensing data to provide the long-term feedback to drivers.

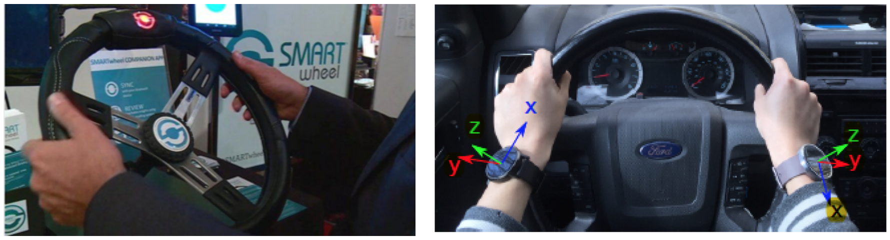


Figure 4.1 Existing work for detecting hands on or off the steering wheel. (1) SMARTwheel system [1] and (2) SafeWatch [2]

4.2.2 Right Hand Motion Sensing

SafeDrive utilizes the inertial sensors on the wrist-worn device (an Android smartwatch) to track and recognize the driver's right hand gestures (as shown in Figure 4.2). The hand motion is defined by 2 parameters according to basic physics - hand (wrist) motion and wrist rotation. As illustrated in Figure 4.3, a driver may move the right hand horizontally from the start point O - the wheel holding position to the position A - center console, position B - front passenger seat, position C - rear seats and position D - driver seat/the steering wheel area, while at the same time vertically (up and down) to reach sun visor, rear view mirror and sun roof control, etc. In addition, the wrist of the right hand rotates around the axis of the forearm, which changes the palm's facing direction to press the touchscreen or button [135]. Based on the inertial sensory data acquired from the smartwatch, the proposed system should be able to measure the hand motion and wrist rotation, and then determine whether the driver is distracted.

SafeDrive targets a series of in-vehicle tasks that may cause distractions during everyday driving such as tuning infotainment systems, drinking/eating, texting and searching personal items, etc. In particular, we suppose that drivers always use the right hand (the hand at the gear-shift side) to handle these tasks. We do the experiment and test in the right-hand traffic country (Canada), if it is in the left-hand traffic countries, we can easily implement the system based on driver's left hand.

Figure 4.2 Detecting hand motion using smartwatch and smartphone.

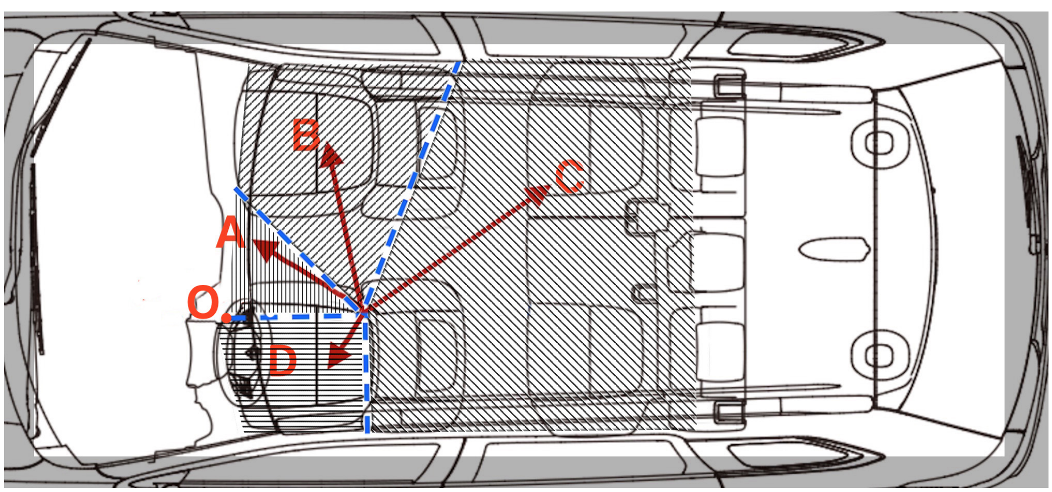


Figure 4.3 Driver Hand Motion Sensing

We acknowledge that many people may wear the watch on their non-dominant hand (e.g., left hand in most cases). The purpose of our study is to help drivers to understand their unsafe (distracted) driving behaviors and help them shape safe driving habits. It could be useful especially for young drivers who are susceptible to distractions such as using smartphones and tuning radio/music while driving. For the driver who already has a smartwatch, the only cost is to switch the watch from the left hand to the right hand (during driving). While it can not only help to save lives on road but also benefit the drivers to reduce damage. In addition, the insurance companies also encourage drivers to install safety applications on smartphones (e.g., Ajusto mobile app [16]) to monitor their driving behavior. Good drivers with higher scores could save up to 25% on their auto insurance premium at renewal. We can see a number of new safety applications using wearables are just around the corner. Why say no to the safety and money?

People who use SafeDrive will be asked to wear the watch on the right hand before driving. In cases when the drivers forget to switch the hand, SafeDrive can remind them in two ways. Firstly, the Driver Detection System proposed by Chu et al. [119, 120] can be used to remind drivers when they enter the vehicle. Their system can determine the enter position of a smartphone user in the vehicle (at the driver seat or passenger seats). Secondly, if the driver missed first reminder, our system can detect smartwatch positions during turns 4.3.3 and remind driver to switch the hand at the next stop. In addition, we assume that drivers will hold the steering wheel (at the position O) properly at the beginning of the trip as well as when they heard alerts. Our prior work [2] is able to detect the driver's hands positions (i.e., on/off the wheel) and send alerts if the hand is not back to the wheel. Above recognition models can be easily integrated in SafeDrive. However, such schemes are not the main contributions considered in this project.

4.2.3 Distracted Driving Scenarios

During everyday driving, there are a number of in-vehicle activities may consistently grab a driver's attention from the road and result in distractions. In this project, we focus on several most commonly occurring in-vehicle activities [169] including fiddling with the control (e.g., infotainment systems), drinking/eating, smartphone use, searching items at passenger side (front) and reaching backseat, as illustrated in Figure 4.4 [1].

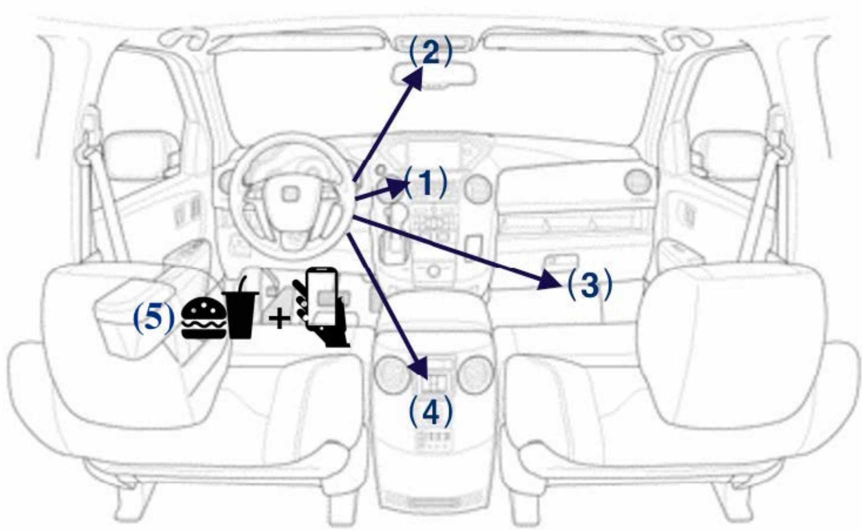


Figure 4.4 In-vehicle distracted activities, 1. fiddling with the control (1) and (2), 2. Dealing with Personal Items/Children (3) and (4), 3. Drinking/Eating (5) and Smartphone Use (6).

[1] The picture of the vehicle is borrowed from the Honda Car Forum website [170]

Fiddling with the control

Fiddling with the control (Figure 4.3 position A) is one of the most common forms of distracted behaviors. In-vehicle systems can now provide the driver with a vast array of advanced functionalities. However, concerns have arisen over the demands on the driver from infotainment systems, and the implications of this for safe vehicle operation. At any given time, more than 600,000 drivers are manipulating electronic devices, like radios/music, navigation, sunroof or reading light, while driving, according to the National Highway Traffic Safety Administration [169]. Such activities require a certain level of driver's attention. If a driver uses the right hand to execute Events (1) and (2) and exceeds a safe period (i.e., 3 seconds) [4], the system should alert the driver.

Searching items at passenger side (front)

Looking for items like CDs/tapes in bags or in the glove compartment at front passenger seat (Figure 4.3 position B) is a common distraction that happens on road. It will take your minds off the road, and at least one of your hands (right hand in most cases) off the steering wheel. SafeDrive should be able to alert the driver as soon as the event is detected.

Reaching backseat

Many drivers are vey likely to be distracted by children riding in the rear seat (Figure 4.3 position C), which are definitely dangerous and can easily lead to serious road traffic accidents. The driver is distracted by the task and not able to notice incoming objects in front of the vehicle such as pedestrians and slow vehicles. The system considers Event (4) as a dangerous behavior and should alert the driver immediately when it is detected.

Drinking/Eating and Smartphone Use

Drinking and eating during driving may seems like a fairly inconsequential act, however it may cause serious consequences for both drivers and other people on the road. It is because that drinking/eating can be a mental overload that diminishes the ability to deal with other traffic events. A study by Brunel University finds that the number of crashes actually doubled with drivers who were eating and drinking behind the wheel [169].

It is no doubt that using smartphone while driving is one of the most dangerous behaviors on the road, which is banned in most of states/provinces in the U.S. and Canada [171]. Though there are a number of applications that monitor and control driver phone use [118, 172], these applications either blindly block calls/text of the smartphones or fails to report the event in time (the smartphone must be on driver-side positions inside the vehicle and it may be already in use).

Other Activities

Besides the aforementioned behaviors, there are many other in-vehicle activities that can take place while driving. For example, the driver may occasionally scratch the head, adjust the eye-glasses, and beep the horn, etc. In practice, it is inefficient to enumerate and distinguish all such arbitrary events, hence SafeDrive regards them all as one category called “other activities”. Though the study for “other activities” is not considered in SafeDrive design, we adopt a simple intuition that any such event can be a safety hazard if they last for over 3 seconds. Our prior work [2] is able to alert the driver as well upon the detection of such long-lasting event. We could merge two systems together to achieve the goal.

In this work, we aim to detect and study distracted driving scenarios metioned above. SafeDrive will use a three-second threshold for Event (1)&(2) and alert drivers immediately when it detects distracted events (3) to (5). The driving activity data is also stored in the smartphone for further analysis (e.g., providing the long-term feedback). We provide the detailed presentation of our system design in the next section 4.3.

4.3 System Design

In order to detect driving distractions, SafeDrive leverages embedded sensors on the smartwatch to track driver’s in-vehicle hand movements, while at the same time uses driver’s smartphone to monitor vehicle dynamics. In this section, we present a detailed discussion of the SafeDrive architecture and algorithms.

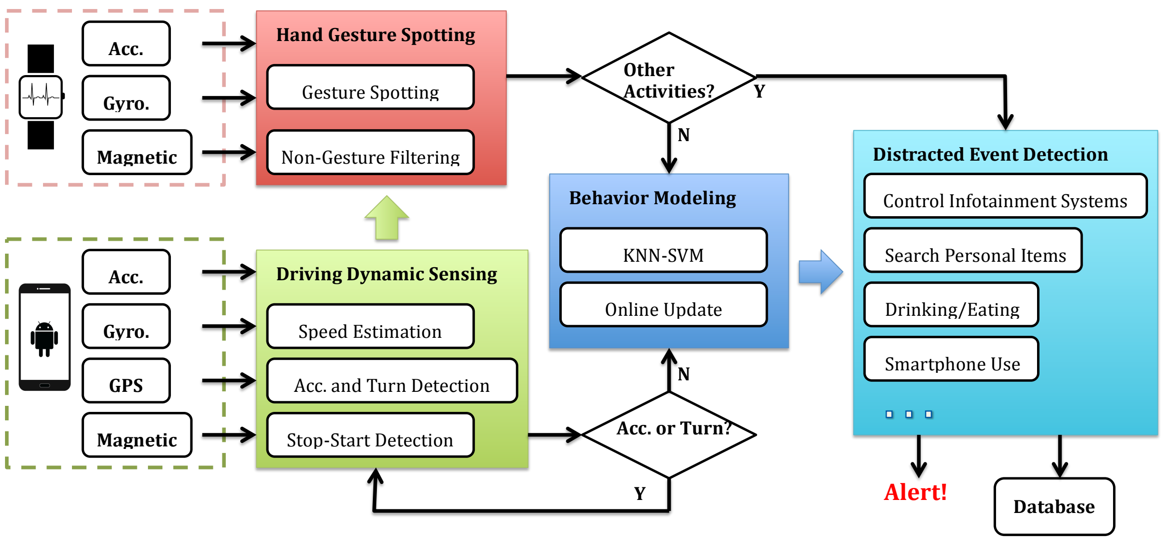


Figure 4.5 System Design

4.3.1 System Overview

The key components of SafeDrive include (1) hand motion sensing and gesture spotting; (2) driving dynamic sensing; (3) hand gesture classification; (4) distracted driving event detection, as illustrated in Figure 4.5.

Hand Gesture Spotting

Sensory data under real-road driving environments includes ambiguity, uncertainty and noise while only a small part of it becomes the object of the recognition model. In addition, different hand gestures with various pattern lengths need to be recognized by using standard stored reference samples [173,174], which makes the gesture segmentation a more challenging task. To handle above issues, a spotting function is employed in SafeDrive to obtain interval candidates from non-gesture movements for hand gesture recognition. We also adopt a rule/experience-based solution that filters out the input if it does not belong to the task domain (e.g., anomalies, acceleration caused by turning) by leveraging the driving dynamic data. In addition, the system spots the wheel turning gesture to determine whether the drivers wear the smartwatch on the right hand. As a result, a segmentation-free 'detection' process is produced, which reduces the false positive rate and computation costs.

Driving Dynamic Sensing

Being aware of the vehicle dynamics is very important to driving event detection. We use accelerometer, gyroscope and GPS on the smartphone to track the vehicle acceleration, rotation rate (angular speed), running speed and location information. The sensing data are used to generate soft hints detecting distracted behaviors and filtering out normal driving hand movements.

Gesture Recognition&Online Learning

We detect driver hand gesture using a KNN-SVM method. The basic idea for our approach is to first use a K nearest neighbor classifier (KNN) to label driver gestures. If K neighbors have different labels (categories), we then use SVM to perform a finer discrimination and determine the gesture category. In our design, both two classifiers are learned offline using the training data (labeled). The gesture X_i is assigned to the class which has the minimum approximation distance. In addition, we also use an online learning method to update training samples in KNN to improve the classification accuracy.

Distracted Driving Event Detection

Recognizing distracted driving events requires the synthesis of the driving dynamic sensing and hand gesture classification. SafeDrive detects and records different distraction events (section 4.2.3) by using one or more rules/thresholds on hand gesture classification outputs, which are developed based on practices. SafeDrive focuses on 5 distracted driving events including touching center console, touching sunroof/reading light control, touching passenger side (front seat), touching rear seat, drinking/eating and picking up a smartphone. When the system detects a distracted driving event, it will send alert to drivers and at the same time store the data in the smartphone for further analysis.

4.3.2 Driving Dynamic Sensing

Good drivers should keep their hands on the wheel and eyes on the road. In SafeDrive scenarios, the driver will hold the wheel and focus on the road ahead during driving, as shown in Figure 4.6. SafeDrive keeps tracking the vehicle speed, acceleration, turning speed and the location data. The smartphone sensor readings are aligned with the absolute coordinate system, Z points towards the sky and is perpendicular to the ground, Y is tangential to the ground at the device's current location and points towards magnetic north and X is defined as the vector product Y· Z, the coordinate systems are shown in 4.6. To simplify the description of our approach, we assume the smartphone's coordinate system is already aligned with the earth.

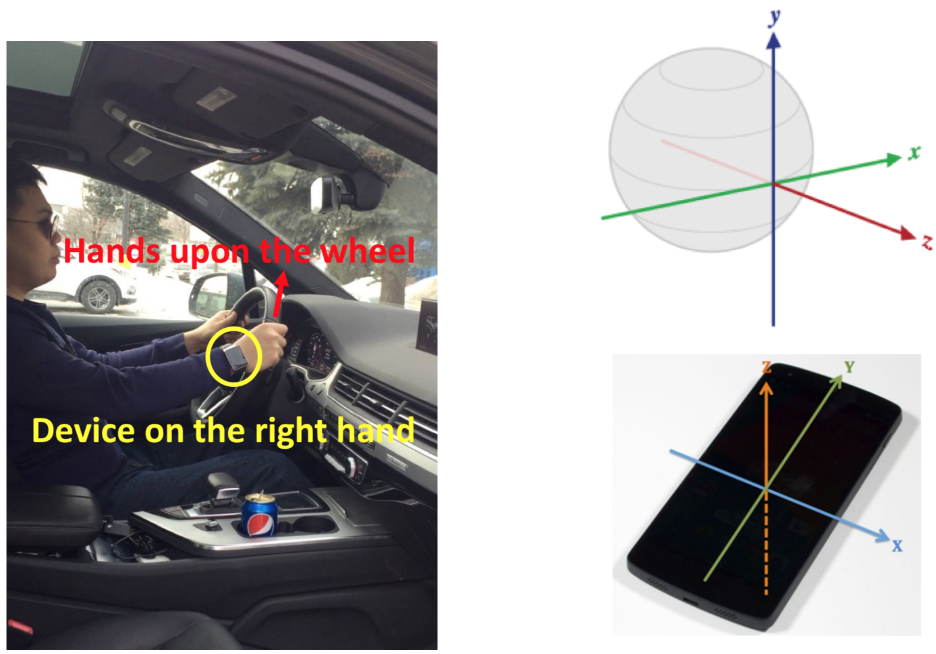


Figure 4.6 Driver in-vehilce scenarios and the earth coordinate system [3] and smartwatch coordinate system

SafeDrive leverages accelerometer values $A = \{a_x, a_y, a_z\}$ in m/s^2 and gyroscope values $G = \{g_x, g_y, g_z\}$ in rad/s to sense vehicle movements. When a vehicle is moving along a straight line, the Z-axis reading of accelerometer reflects the moving accelerations, the a_z is positive when the vehicle brakes, and vice versa. The gyroscope data is the indication of rotation movements. The angular speed g_x - the X-axis reading of the gyroscope reflects the turning speed and turning directions of a vehicle. It generates positive reading when the vehicle is turning left, and a negative reading during a right turn. According to Wang's study [118], we set 0.5 rad/s as the threshold in turn detection.

In addition, we also use the vehicle speed and acceleration to determine whether the vehicle is moving or stop [2]. It can help us to better manage the system and trigger other functions like switch off the detection to save energy, reminding user to wear the smartwatch on the right hand, etc.

4.3.3 Hand Gesture Spotting

Gesture Spotting and Feature Extraction

As discussed in section 4.2.2, the in-vehicle activities can be indicated by different positions of the driver's right hand/wrist. For example, a driver may move the right hand from the steering wheel position O to the center console A to tune the radio or open the sunroof (2), to the passenger side (front seat) B or rear seats C to reach a bag, and to the wheel area D to beep the horn, etc.. Therefore, the most straightforward method for spotting a gesture is to track the path of driver's right hand movements by using acceleration data. However, directly using multiple integration over hand acceleration data obtained from the smartwatch IMU sensors may always be affected by the randomness of noise and result in large deviations from the true distance value [84, 135]. On the other hand, an interesting observation in the experiment is that the movements of driver's right hand in the vehicle approximately follows a circle, which enables us to use different angle values to represent position A, B, C and D in the horizontal (X-Y) plane. Moreover, the results in work [35,135] show that the angular velocity measured by smartwatch gyroscope could achieve reasonable accuracy. Inspired by this simple yet useful finding, we seek to locate driver's hand and spot gestures by using the integral of smartwatch gyroscope input on the horizontal (X-Y) plane.

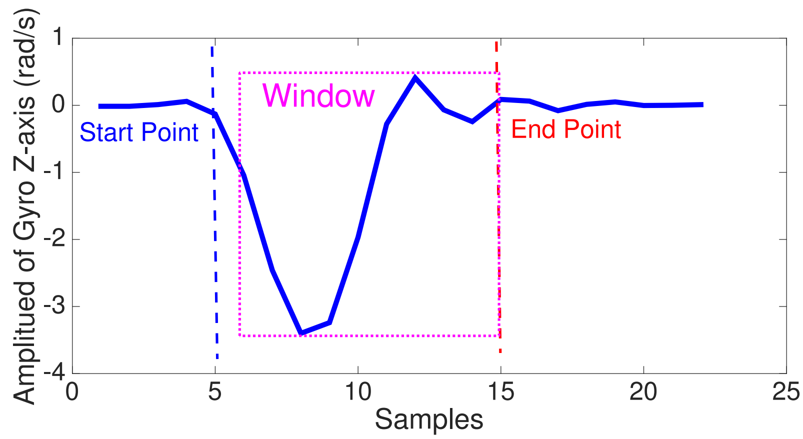
SafeDrive uses inertial sensors (i.e., 3-axis accelerometer, 3-axis gyroscope and magnetic) on an Android smartwatch (Samsung Gear Live) to collect user hand motion data. In order to measure the forearm rotation in the vehicle, the smartwatch sensor data are also aligned with the Earth coordinate system (gravity extracted) and the Z-axis readings of gyroscope is used to represent the hand/wrist angular velocity on the horizontal (X-Y) plane. If a driver's right hand moves from O to A , B or further to C, the Z-axis reading is negative, otherwise (to D) is positive. Once the absolute value of angular velocity exceeds the threshold (greater than 0.1 rad/s) the gesture spotting function is triggered, which employs a sliding window of 1.0 second on sensor readings with a 10 Hz sampling rate. The length of the window buffer has been proved to be effective to capture normal human in-vehicle activities in the real-road test and the detection latency is discussed in section 4.4.6.

Based on the sensing data (the Z-axis reading of gyroscope) stored in the window buffer, SafeDrive estimates the angle change of the driver's right hand. If the accumulation of angular velocity (the integration result) reaches the peak value, the system will stop the spotting process and use the last sample as the gesture end point. In addition, the angle change should be greater than a certain threshold (0.45 rad at position A), otherwise it is considered as noise by the system. Figure 4.7 shows an example of the gesture spotting function. A driver is moving his hand from the steering wheel O to the front passenger seat B. The spotting process starts from the sample No. 5 and stops at the sample No. 15. As we can see in Figure 4.7(a), the interval candidate (window) obtains the major characteristics of the gesture pattern. Therefore, SafeDrive is able to extract features from different length hand gestures based on the spotted intervals. The extracted features includes mean, standard deviation, root mean square, and mean crossing rate of each axis of accelerometer, gyroscope and the derivative of magnetic. The features will be sent to recognition models. For any other gestures spotted in D, we only use the threshold to pick it out and classify as other in-vehicle activities refothers.

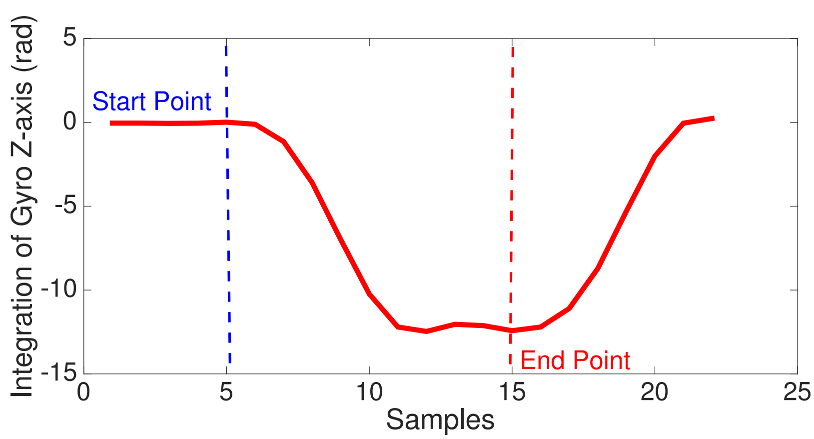
Smartwatch Position Determination

When a driver makes a turn, we can use wrist rotation measurements to infer steering wheel turning angles [35]. As shown in Figure 4.8, the X-axis of gyro reading from smartwatch (smartwatch coordinates) reflects the wrist rotation while the Z-axis of gyro reading from smartphone (world coordinates) reflects the vehicle motion (turns). In this work, we calculate driver's hand rotation angle values when the system detects turns based on vehicle dynamic sensing data. The basic insight of our method is, during the vehicle turn, the rotation readings from the smartwatch on different hands (left and right) will be opposite when we are using the smartwatch coordinate system, as illustrated in Figure 4.8.

We implemented the hand rotation estimation by drawing the idea from the work [35]. Based on the result, we are able to determine whether the driver is wearing the smartwatch on right hand and remind driver to switch the hand (at parking mode) to promote safety.



(a) Gesture Start Point



(b) Gesture End Point

Figure 4.7 An Example of Gesture Spotting. (a) Start point sensing using angular velocity. (b) End point sensing using integration.

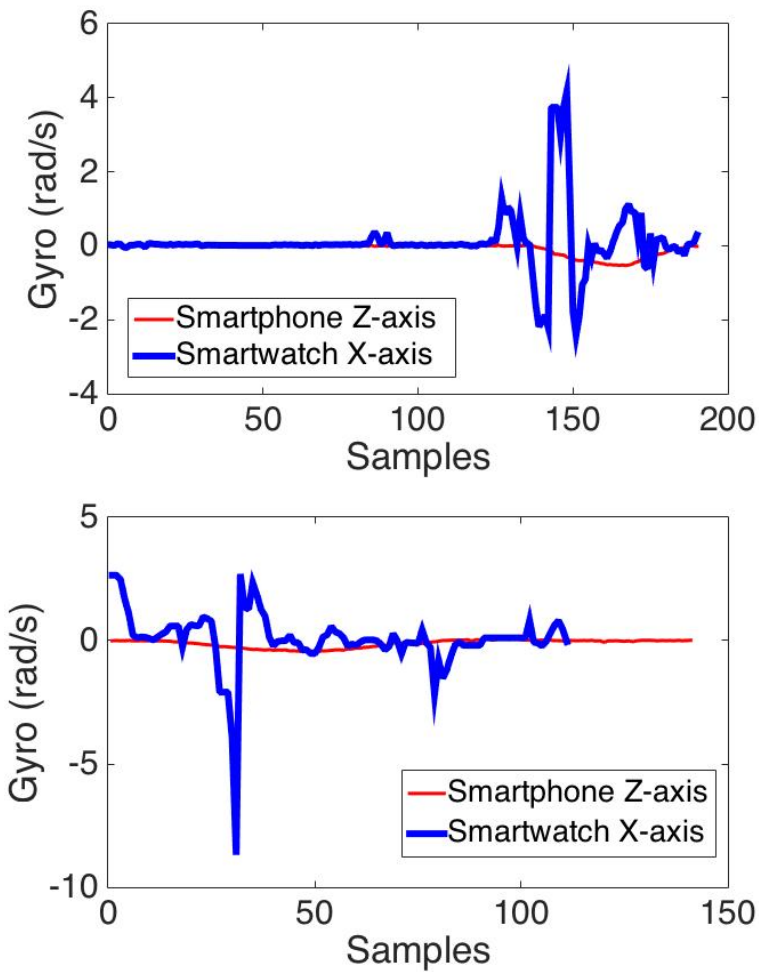


Figure 4.8 Smartwatch position determination. 1. The smartwatch coordinate system, 2. Samples of X-axis gyro-readings on driver's right hand during a right turn, 3. Samples of X-axis gyro-readings on driver's left hand during a right turn.

Normal Driving Gesture Filtering

A driver often needs to turn the steering wheel or shift the gear (although there is less manual transmission cars on road, most of automatic ones have manual mode and we do not consider on-wheel transmissions) in real driving environments. These normal-driving hand movements are easy to be wrongly detected as distracted behaviors due to similar gesture patterns. In this work, we leverage smartphone sensing to generate soft hints filtering out such movements.

When a driver rotates the wheel, he/she may make a turn, aggressive lane changing or standard lane changing. Our system can detect first two events by using driving dynamic data as discussed in section 4.3.2. For a standard lane changing, driver's hand movements do not exert enough force or rotation on the device to distinguish from noise [12], which will not be spotted. On the other hand, though the gear shifting is a normal driving behavior. The driver has to move the right hand from O to A. SafeDrive will also alerts driver if the he/she takes a long time period on this task as same as other distracted events (e.g., tune the radio).

4.3.4 Gesture Recognition

In this project, we consider four basic hand motion/gestures including right hand from O to A ((1) control and (2) sunroof), from O to B ((3) front passenger seat) and from O to C ((4) rear seat). The right hand from O to D is considered as other activities. For drinking/eating and smartphone use detection will be discussed in section 4.3.5.

KNN-SVM Classifier

In this work, we employ a KNN-SVM method to classify different distracted driving behaviors. Support vector machine (SVM) is a popular model and has been widely applied in human activity recognitions [175]. It achieves very good accuracy in our static testing scenarios. However, SVM struggles to achieve the bias-variance balance and is prevented from better accuracy in real-road scenarios due to the small sample dataset. Since the vehicle conditions changed significantly (participants sit at rear seats in a moving vehicle.). In our test, there always exist confusions between gestures which have similar hand positions such as O to A vs O to B, or O to B vs O to C.

On the other hand, the K nearest neighbor (KNN) technique is renowned for its simplicity and theoretically bounded performance when the size of the sample set increases [176]. Because the relationships of neighborhood can be computed on the go without the need of a pre-trained model, KNN is sometimes referred to as a lazy-learning algorithm. Though its performance can not beat the SVM model in most cases, such lazy-learning characteristic allows us to update the model incrementally when new user data come in, which can help to improve the system detection accuracy in our tests.

Inspired by the finding, we propose a two stage KNN-SVM classifier. At the first stage, KNN classifies most of the data samples with a high accuracy, and allows us to incrementally update it with new data samples. For those data samples who has closely voted top neighbors, they get to the second stage, where pre-trained SVM binary classifiers are adopted to decide which top voted neighbor should be used to label the target data. We also considered other classification algorithms for the second stage, but our experiments in Sec. 4.4.4 prove SVM to be the best choice.

In summary, with a new incoming data sample, SafeDrive does the following:

1. Compute distances of the input vector to all training examples and pick the nearest K neighbors;

2. If the K neighbors have the same label, the vector is labeled and exit; else, take the top two different labels within the K neighbors.

3. Apply the binary SVM corresponding to the chosen labels.

4. Use the SVM result to label the input vector.

In our implementation, the Euclidean distance is used, and we apply the quadratic kernel versioned SVM.

Online Learning and Classifier Update

As the new data coming in, the pre-trained classifier may become outdated and fail to reflect the changing dynamics of driving behaviors. Therefore it is important to update the classifier periodically. The straightforward way is to retrain the classifier with the updated dataset. Intrinsically, this is not a problem for KNN since it is a lazy learning algorithm and all computation is supposed to happen only at the moment of classifying (compute all the neighbors). However, as we update the dataset, the classifying cost will eventually become a problem due to too many pair-wise distances to evaluate. Therefore we need a mechanism to eliminate outdated data entries and keep the dataset at a reasonable size.

The simplest way of keeping the dataset at a particular size is making it as a FIFO queue, so that the oldest data sample always gets removed. This may cause problem because for the outlier samples are not necessarily older than regular ones. If we assume the same driver will not have abrupt changes in his/her driving habits, then we should try to remove the outliers, hence simply eliminating oldest data sample is not safe.

To address this problem, we borrow the CH index idea from the clustering problem [177]. When we want to cluster a bunch of data points into different classes, CH index evaluates the clustering result, it is defined as,

$$CH_K = \frac{trace(SSB_K)/(K-1)}{trace(SSW_K)/(N-K)} \ .$$

Here, K is the number of clusters, $N = \sum_{i=1}^{K} N_i$ is the total number of data points; SSW (within-cluster scatter matrix) and SSB (between-cluster scatter matrix) are defined as follows,

$$SSW_K = \sum_{i=1}^{K} \sum_{x \in C_i} (x - m_i)(x - m_i)^\top,$$

$$SSB_K = \sum_{i=1}^{K} N_i (m_i - m)(m_i - m)^\top.$$

where C_i is the ith cluster; m_i is the center of C_i; N_i is the number of points in C_i; m is the mean value of all points in the data set.
The numerator of the CH index describes the dispersion between the clusters, and the larger it is, the further different clusters are from each other. This means that the difference between these clusters are more obvious. In contrast, the denominator describes the dispersion within each cluster, and the smaller it is, the closer each element is to others in the same cluster. This indicates higher similarity among elements within the same cluster. And in conclusion, the higher the CH-index is, the better the cluster result is.

Come back to our problem about updating the dataset, each time when SafeDrive needs to eliminate a few old data points, we calculate the CH-index after removing each one of them, and eliminate the data points that leads to lower CH-index. We need to point out that, the class center m_i and dataset center m in SSW_K and SSB_K can be easily updated upon each new data point, thus the total cost of validating the CH-index is negligible.

4.3.5 Distracted Driving Event Detection

SafeDrive aims to recognize four types of dangerous distracted driving events (detailed in section 4.2.3). For each type, we describe the series of rules used to interpret different gestures inferred by the classifiers that allow dangerous distracting events to be detected. The detection system is activated while the car is moving forward (while a positive speed is reported by the stop-start detector and not turning as reported by the turn detector). In addition, we assume that the driver only perform one single distraction activity at a time. (as shown in Figure 4.9)

Interacting with infotainment systems

SafeDrive detects two types of scenarios of interacting with the vehicle infotainment/assistance system including gesture 1 O to A (1) touching center console and gesture 2 O to A (2) touching sunroof/light control. Since the time limit is 3 seconds and there will be around 1s delay on detecting each driver's hand moving gesture. The total time left for the activity is two seconds. Thus, if a driver does not move the right hand back to the wheel in two seconds after the detection of a distracted gesture (1) or (2) then a dangerous distracted driving event is inferred.

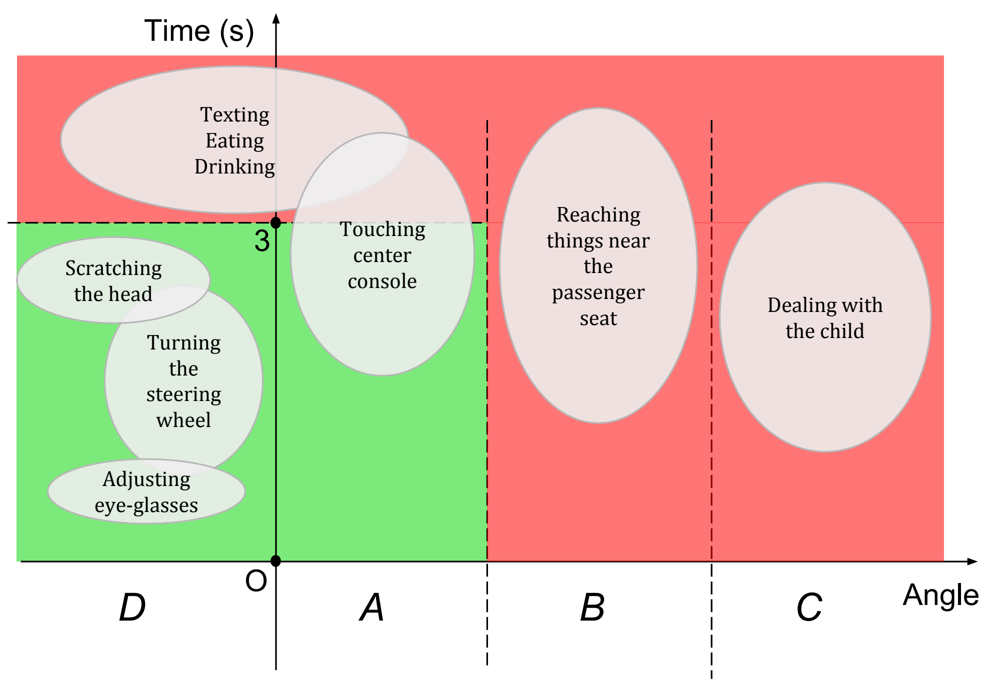


Figure 4.9 Distracted Driving Event Detection Scheme. Activities in green areas are safe and in red areas have potential risks.

Dealing with Personal Items/Children

A driver may deal with personal items or children using gesture 3 (O to B) or 4 (O to C), unlike interacting with infotainment systems, SafeDrive will report such distracted behaviors immediately once they are detected. In the experiment, it shows that gesture 4 (rear seat) is less distinguishable in dictionary learning compare to other gestures. When a driver moves the hand to the rear seat, it combines various accelerations and rotations which make the event vector x more complex. On the other hand, we observed that moving hand to the rear seat produces a significant angle change in the gesture spotting step (shown in Figure 4.3). The system achieves a good detection rate by adding this value as a primary feature.

Drinking/Eating and Smartphone Use

Detecting drinking or eating on road is very important for driving safety. As same as gesture (3) and (4), the system alert the driver directly without any waiting time. In this work, the drinking/eating event may consist of two gestures: 1. (hand) moving to the drink/food/smartphone and 5. pick up the drink/food/smartphone (gesture 5 from A to D). We assume that the drink/food is placed at or near the cup holder (position A). Gesture 1 shares the same spotting threshold with gesture O to A (1) (touching center console) as they have similar coordinates in the (X-Y) plane. Once the system spots the gesture 1, it will check two neighbor (the current and next) windows to detect both 1 and 5, for gesture 5 it has a much larger reverse angle change compare to 1. We measure the angle difference between 1 and 5, and set a threshold to detect gesture 5. If there is no gesture 5 detected, the system regards the event as interacting with infotainment systems and switches the rules.

Discussion

In this paper, we focus on detecting driver behaviors after moving hands off the wheel. Tracking "static" positions of driver hands or determine whether the hand is back to wheel is not considered in SafeDrive. In order to hold this case, we have another work [2], which monitor driver hand conditions (e.g., on or off the wheel, resting on the leg) by detecting driver hand/forearm postures. These two works can be merged together to present a comprehensive study of driver in-vehicle activities.

4.4 Evaluation

In this section, we evaluated SafeDrive in different vehicles under parking and driving conditions. Specifically, we first describe the experiment setup and datasets, then present the results of gesture spotting, normal activity filtering, hand gesture detections. Moreover, we examined the performance of the online updating method, we also analyzed the power consumption and system latency in the experiments.

4.4.1 Experimental Setup

Data Collection

We implemented SafeDrive on a Samsung Gear Live smartwatch with a Quad-core 1.2 GHz Cortex-A7 cpu, 512 MB RAM and a Google Nexus 6 Android smartphone which is equipped with a Quad-core 2.7 GHz Krait 450 CPU , 3G RAM. We manually labeled ground-truth driving events and the system detection results. The raw data (driving dynamic and hand motion information) were stored offline for further analysis. In our experiments, we recruited 20 participants - 10 females and 10 males from age 25 to 35. There are 5 different types of vehicles involved in the study including a sedan (Ford Focus), a compact SUV (Jeep Compass), a mid-size SUV (Audi Q5), a minivan (Honda Odyssey) and a full-size SUV (Audi Q7).

Participants were asked to perform five different gestures including: (1) reaching centre console , (2) reaching sunroof button, (3) reaching passenger seat (front), (4) reaching backseat and (5) drinking water and (6) smartphone use, as illustrated in Figure 4.4. We asked them to do (10 times per gesture) at the driver seats in the static vehicle (in a parking lot) and the real-road driving test (10 times per gesture as well). We also ask participants to perform extra 5 times per gesture in the real-road driving test to examine the performance of our online updating method (presented in the next section 4.4.1).

We assume that drivers will follow the instructions to keep safe, so all gesture are start from the steering wheel. At the beginning, the participant will hold the steering wheel put the hands on 3 o'clock and 9 o'clock positions. Each time the participant performs a gesture, he/she will move the right hand from the steering wheel to the target locations (1)-(4), then move back to the steering wheel at 3 o'clock. Gestures (5) and (6) are consecutive actions, the participant first move hands to the cup holder (in the middle of the car) and then pick up the food/drink or smartphone to the his/her mouth. After that they put the objects back to the cup holder and move hands back to the steering wheel still at 3 o'clock.

Participants were suggested to use their own vehicles, we also provided vehicles if they do not have one. The total maximum duration of the study for each participant is around 50 - 70 minutes. Our project has received IRB approval.

Real-Road Driving Scenarios

Since it is unsafe and illegal to ask a driver to perform a series of hand gestures while driving. We therefore provide simulated real-driving scenarios at backseats in a moving vehicle. One of our researchers (holding a valid driver license) drove the vehicle (the mid-size SUV), the participants were asked to sit at the driver-side backseat and wear the smartwatch to perform a series of hand gestures including touching center console, touching sunroof/reading light control, touching passenger side (front seat), reaching rear seat (the trunk), picking up a smartphone and drinking/eating. The real driver in the vehicle will only focus on driving and will not join any part of the test. We also select a driving route (8.0 km) with less traffic and good road quality to reduce the risk of accidents, as shown in Figure 4.10.

More specifically, 1. We ask the participants to hold a steering wheel model (a round plastic plate) to simulate the driving body pose. 2. We use an Android tablet device as the car instrument panel. The tablet device is placed at the backseat air condition port (in the middle of the vehicle), the participants will touch the device like a driver to switch music, use navigation, etc. 3. The participants will be asked to touch the light button on the roof just like a driver to control the reading light/sunroof. 4. We also put a bag on the right side of the backseat, the participants will be asked to touch an item in the bag. 5. We also individually fold the backseat at the other side, the participants can move the right hand through it to touch an item in the trunk. 6. We put a water bottle in the backseat cup holder, the participant will be asked to prick up the bottle like drinking. 7. The participant will be asked to pick up the smartphone from the cup holder at backseats.

We acknowledge that the rear seat is not a real driver seat, however, since real drivers may use different type of vehicles on road. A rear seat simulation is just like a different vehicle which will not affect the experiment significantly. In addition, there may be psychological (and possibly physical) differences between the real driving on road and the in-vehicle experiments, which could affect participants' gestures. However, asking a participant to perform any unsafe behavior while driving is irresponsible and illegal. To handle this issue, a further study is considered which will recruit participants to wear the smartwatch with SafeDrive installed for long-term monitoring on their daily driving.

Figure 4.10 Real Driving Routes

Table 4.1 Normal Driving Event Filtering

Driving Event	# of FPs	# Hours
Driver 1	21	over 20
Driver 2	17	over 10

Metrics

To evaluate the system performance, we use the confusion matrix to present our results. We also define the metrics including true positive (number of driving events that are correctly identified), false positive (number of unrelated objects are classified as target events), Accuracy (number of correctly classified samples/number of samples being tested). Table 1-5 provide the detailed results across all scenarios.

4.4.2 Normal Driving Event Filtering

To evaluate non-distracted gesture filtering, we conduct experiments using the smartphone for over two weeks in downtown areas. The smartphone was placed in the cup holder (it can be at any place in the vehicle as we aligned it with the earth coordinate system). Each of the traces contains over 30-minute of driving. We tested normal/slight turns, strong/significant turns and strong/significant lane changing events. As discussed in section 4.3.3, we do not consider slight lane changing event as it will not be spotted as a gesture at next step. Table 4.1 summarizes the details on normal gesture filtering, it shows that our proposed system is able to filter out the unrelated gestures to improve the detection accuracy.

Table 4.2 Hand Gesture Spotting

Gestures	# of TPs	# of FPs	# of FNs	# of GT
Gesture 1	186	11	14	200
Gesture 2	195	7	5	200
Gesture 3	193	3	7	200
Gesture 4	195	5	5	200

4.4.3 Gesture Spotting

In order to test the gesture spotting algorithm performance under real-driving conditions, we use two groups of participants: static/parking (10) and driving (10). We also ask participants to do some normal gestures like scratching head, adjusting the glasses or slightly turning the wheel. Such normal gestures could be detected as false positives in the test, however, is not easy to simulate in moving vehicles (e.g., turn the wheel). Thus, the ground truth of gestures is 200. In addition, two researchers worn the watch and did the real driving for over 30 hours, to test if the system will have large false positives. Table 4.2 shows true positives and false positives of our gesture spotting algorithm. The threshold for gesture spotting are determined based on the test using the training data.

4.4.4 Distracted Driving Behavior Identification

In real-road experiments, we examined the ability of SafeDrive in detecting basic gestures in static/parking mode and driving mode. We explain the experiments from the following perspectives.

Training set and test set

We have 20 participants and collect their data in two ways: *Static/Parking* and *Driving*. The *Static* data are collected from participants sitting in the driver seat in a static vehicle. The data in the driving mode are collected when the participants are in a moving vehicle simulating the test gestures. In the application context of SafeDrive, the static data corresponds to those user data we have already collected in a simulated environment and the driving data corresponds to the real world user data which needs to be classified and can be used to update our system on the go.

Therefore, we have the following training and test settings to evaluate gesture classification.

- Training(*20 Static*), Test(Cross Validation): We use a 10-fold cross validation to test the classification models k-NN and SVM as shown in Table 4.3, Table 4.4 and Table 4.5.
- Training(*20 Static*), Test(*20 Driving*): Test how the simulated gestures can capture the characteristics of gestures in real driving conditions as shown in Table 4.6 and Table 4.7.
- Training(*20 Static + 20 Driving updates*), Test(*20 Driving*): Test how the simulated gestures can be generalized to new user's gestures using online update method in real driving conditions as shown in Table 4.8.

As we can see in Table 4.3, Table 4.4 and Table 4.5, SVM could achieve better results than KNN and KNN-SVM in the 10-fold cross validation using training data, KNN-SVM is close to SVM but not better.

However, since participants sat on rear seats of the vehicle, the space condition changed significantly. It is like that they sat in a sedan in static scenarios, while use a truck to test in real-road scenarios. Both SVM and KNN methods become worse (KNN is much worse). KNN-SVM beat SVM because it can use new data collected from real-road scenarios. Though the improvement is not significant yet due to less testing time. It still has great potential to achieved a much better results in long-term running, since driver will use the system and the dataset will be updated everyday.

Table 4.3 Confusion Matrix for: k-Nearest Neighbor static, overall accuracy 92.8

True\Predicted Class	Gesture 1	Gesture 2	Gesture 3	Gesture 4
Gesture 1	186	12	2	0
Gesture 2	16	184	0	0
Gesture 3	15	0	184	1
Gesture 4	0	0	12	188

Table 4.4 Confusion Matrix for: Support Vector Machine static, overall accuracy 95.5

True\Predicted Class	Gesture 1	Gesture 2	Gesture 3	Gesture 4
Gesture 1	180	19	1	0
Gesture 2	5	195	0	0
Gesture 3	5	0	194	1
Gesture 4	0	0	5	195

Table 4.5 Confusion Matrix for: KNN-SVM static, overall accuracy 94.2

True\Predicted Class	Gesture 1	Gesture 2	Gesture 3	Gesture 4
Gesture 1	184	14	2	0
Gesture 2	9	191	0	0
Gesture 3	10	0	189	1
Gesture 4	0	0	10	190

Table 4.6 Confusion Matrix for: Support Vector Machine real road, overall accuracy 91.5

True\Predicted Class	Gesture 1	Gesture 2	Gesture 3	Gesture 4
Gesture 1	171	2	27	0
Gesture 2	6	195	0	0
Gesture 3	10	2	187	1
Gesture 4	2	0	18	180

Table 4.7 Confusion Matrix for: KNN real road, overall accuracy 83.1

True\Predicted Class	Gesture 1	Gesture 2	Gesture 3	Gesture 4
Gesture 1	168	10	22	0
Gesture 2	27	173	0	0
Gesture 3	36	0	155	9
Gesture 4	0	2	29	169

Table 4.8 Confusion Matrix for: Online KNN-SVM, overall accuracy 95.1

True\Predicted Class	Gesture 1	Gesture 2	Gesture 3	Gesture 4
Gesture 1	189	4	7	0
Gesture 2	5	195	0	0
Gesture 3	7	2	190	1
Gesture 4	1	0	12	187

Table 4.9 Distracted behavior detection

Gestures	# of TPs	# of FPs	# of GTs
Gesture 5 (Static)	191	9	200
Gesture 5 (Driving)	182	18	200

Complex Gestures

Table 4.9 shows the results of gesture 5 (drinking/eating and smartphone use) detection. Since gesture 5 consists two steps (basic gestures) - 1. moving hand from O to A (gesture 1) and 2. pick up gesture. We first use KNN-SVM directly to detect gesture 1 and employ a single threshold solution (as similar as our spotting method) for pick up gestures. In addition, we do not employed online update scheme. Because it is hard to distinguish step 1 and 2 while we need to update them separately. Therefore, the error rate and FPs increased, especially for real driving conditions. In our cases, we only detect whether a user will move his right hand from A to D. Moreover, our assumptions for pick up gestures are still naive and may fail to obtain hidden information from the training data. The accuracy will be affected by the detection result of gesture 1, since we can not detect step 2 without step 1. We will continue our study on such in-vehicle activities considering complex real driving cases.

4.4.5 Power Consumption

We measure the total power consumption of the SafeDrive on smartwatch by recording its battery life. The smartwatch used in experiments was able to keep sensing and transferring data (via Bluetooth) up to 7 hours (screen off) and 3.5 hours (screen on). Other smartwatches such as Sony and Moto 360 G series, the battery life is around 5-7 hours. The battery life can be further extended by altering the usage conditions (e.g., switch off sensing when the vehicle stops). We assume that most of users would switch off SafeDrive and be able to charge the smartwatch when they are in the office or at home. Since SafeDrive is only used when the user is in the vehicle and the journey will less likely to be significant long, it is capable of recording driver behaviors for everyday driving. In addition, the smartphone is used to sense vehicle motion and run heavy processing tasks. The SafeDrive Android application utilizes an average of 6.52% of the smartphone CPU. We do not consider smartphone battery lifetime as it can be charged in the vehicle.

4.4.6 Detection Latency Analysis

Gesture detection

In this section, we discuss the system detection latency on gesture spotting and gesture classification 4.11. Distracted gesture classifications rely on the gesture spotting and normal gesture filtering. SafeDrive employs a sliding window (1.0 second) along the temporal axes of sensor readings to define an driving event. To spot a gesture, the system uses the integral of smartwatch gyroscope's readings (z-axis) to estimate the angle change. Considering the time limit (3 seconds) and the smartphone processing time, it may take a little bit more than 1 second. For the one-gesture driving events (e.g., O to A), the total time left for the activity recognition (interacting with console) is slight less than 2 seconds. For the multi-gesture events (e.g., drinking, smartphone use), it may take around 2 seconds for the system to spot the gestures, our system still have 1 second left. However, if we change the sliding window to 1.5 seconds (1.2s or 1.3s is meaningless), the total latency will exceed 3 seconds which is unsafe for drivers.

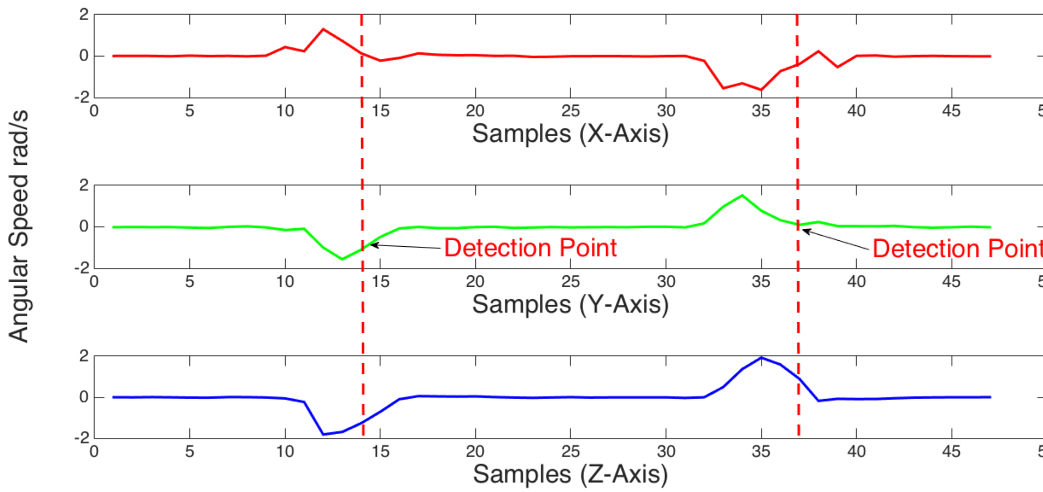


Figure 4.11 Gesture Spotting Latency

Turn detection

In order to detect a turn movement of the vehicle, the system needs to measure the Z-axis (earth coordinates) gyroscope reading of the smartphone. As illustrated in Figure 4.12, if a driver turns the wheel the system will first spots a gesture. Then the system could detect a turn movement in 1.0 second and cancel the distracted gesture recognition.

4.5 Limitations

In this section, we discuss the limitations in the presented work and the extensions that SafeDrive can be deployed in the future.

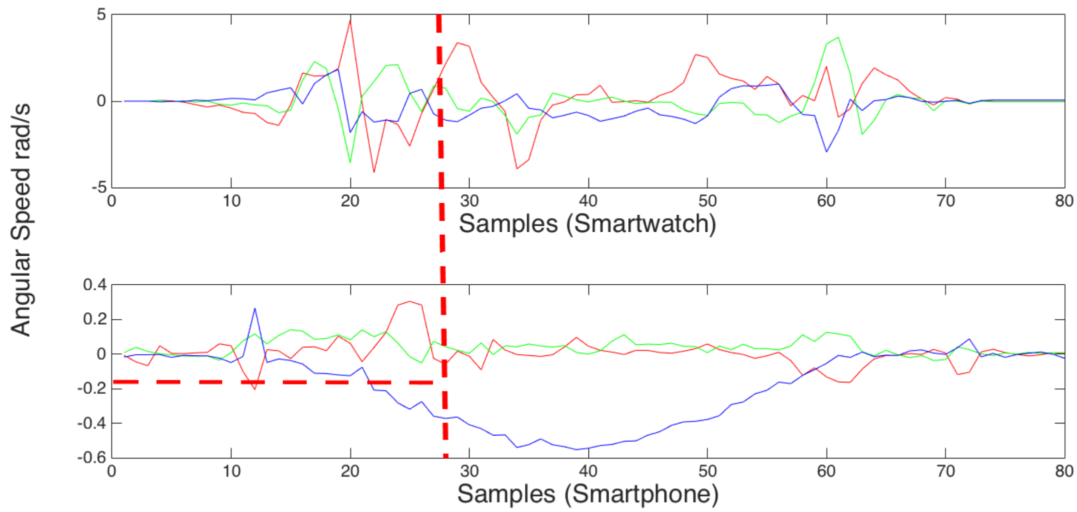


Figure 4.12 Normal Driving Gesture Filtering Latency

4.5.1 Smartwatch Position Detection

In order to detect the driver's distracted behaviors, we asked participants to wear the smartwatch on their right hands (the gear-shift side). Though SafeDrive is able to detect and remind driver if the smartwatch is not worn at the right hand, drivers may still ignore the alerts and do not switch properly. To handle such issues, we may combine SafeDrive with another work [2] to provide a comprehensive study on in-vehicle driver behaviors. The system will be able to examine how a driver holds the wheel (holding position), whether he/she is smoking behind the wheel, as well as enable honk detection by using the microphones on smartphones.

4.5.2 Smartwatch Battery

Though we already provide a lightweight system design, user may still receive a low-battery warning on road, especially if there is no proper charger adapter in the vehicle. A better energy management scheme is desirable to improve the system efficiency such as moving/parking-mode detection (only update the data at parking mode) and sending alerts using smartphone speaker only when the battery is low. On the other hand, since in-vehicle wireless charging technology is becoming more and more popular, it has been considered as an alternative solution for this issue.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

Traffic accidents are perceived as one of the major societal problems in the world today. The road traffic is the result of interaction between people, vehicles and road infrastructure [41, 178, 179]. In this process the human is a key element, but also the weakest link. Changing/shaping driver behaviour is considered as one of the most effective ways to counteract traffic accidents and promote road safety. As an important and emerging subject in both research and industry communities, advanced driving assistant systems (ADAS) have drawn great attention in recent years. These technologies not only have function to greatly increase comfort and efficiency of driving, but also help to avoid accidents by assisting the driver in their tasks continuously.

In this thesis, we delved into the driving safety issues by leveraging smart sensing techniques. To achieve the objectives, we use embedded sensors on mobile devices (e.g., smartphone and smartwatch) to track vehicle motion and driver behaviors, while at the same time adopt machine learning algorithms to recognize different driving activities. Besides, we review the existing ADAS approaches on dangerous driving event detection and driver behavior analysis, and discuss how our research advances the state of the art. With a comprehensive understanding of related work, we explained the drawbacks of the existing studies and distinguish the advantages and novelty of the algorithms, models and frameworks proposed in this thesis.

The literature has shown that most of driving event detection and risk assessment systems trigger the alert only when the situation becomes dangerous and thus when an accident is imminent. Some studies have highlighted the negative effects that ADAS can sometimes have on drivers, for instance in term of emotions, demand for visual contact, and less time to react [180, 181].

Surrounding objects may also be directly impacted by the consequence of an alert lately or not well interpreted by the driver. In addition, these studies have shown that early warnings improve the efficiency of the alerts [28]. Thus, the main challenge of a driver safety system remains the responsiveness of the detection and the integrity of generated information. We should detect the dangerous driving conditions as early as possible and provide prompt feedbacks to drivers, so that the system can become preventive instead of remedial.

In particular, two studies are presented in this thesis: 1. SafeCam - analyzing intersection-related driver behaviors using smartphone sensors, and 2. SafeDrive - detecting distracted driving behaviors using wrist-worn devices (e.g., smartwatch). We summarize these two approaches as follows:

In the first study, we propose SafeCam, an effective smartphone application that detects and recognizes driver unsafe behaviors at intersections. SafeCam does not rely on external hardwares in the processing. It actively records a number of events including unsafe turns, braking, speeding, stop signs/red light infractions and lane drifting problems. In the experiments, SafeCam is robust and effective in various real-road driving environments. The proposed system is able to effectively detect and alert drivers in real-time for their dangerous behaviors at intersections.

In the second study, we propose SafeDrive, a wrist wearable sensing based application that detects driving distractions by tracking driver hand motion. It adopts machine learning algorithm to recognize driver distracted behaviors, while at the same time utilizing smartphone sensing to generate soft hints filtering out anomalies and non-distracted hand movements. SafeDrive does not rely on additional wearable sensors or custom instrumentation in the vehicle. It actively records a number of distracting activities that most commonly occur in the vehicle including interacting with infotainment systems, drinking/eating, texting and searching personal items. In real-road experiments, the overall accuracy of SafeDrive is promising, which could recognize different in-vehicle unsafe activities and thus prevent distractions.

We explore the technical feasibility of SafeCam and SafeDrive to contribute to driving safety. The experiment results demonstrate that both these systems have great potential to help drivers to shape safer driving habits and prevent unsafe driving conditions to avoid car accidents. The functional performance of our proposed systems as considered in this thesis is only a foundation. The driver hand motion and vehicle dynamic data are indicative of accident risk and can be utilized to incentivize risk-minimizing behaviors among drivers. Both researchers and practitioners should make use of such information, which not only to reduce claims costs and reward insurance customers, but also to increase overall traffic safety and save human lives.

5.2 Future Work

In real-road experiments, the overall performance of both SafeCam and SafeDrive are promising, and thereby encourage us to further our study to enhance driving safety. In this section, we point out several specific points as to how the detection system can be improved considering both efficiency and effectiveness factors. We also discuss our findings towards research challenges arising in the domain of driver safety applications and the potential extension work that can be deployed in the future.

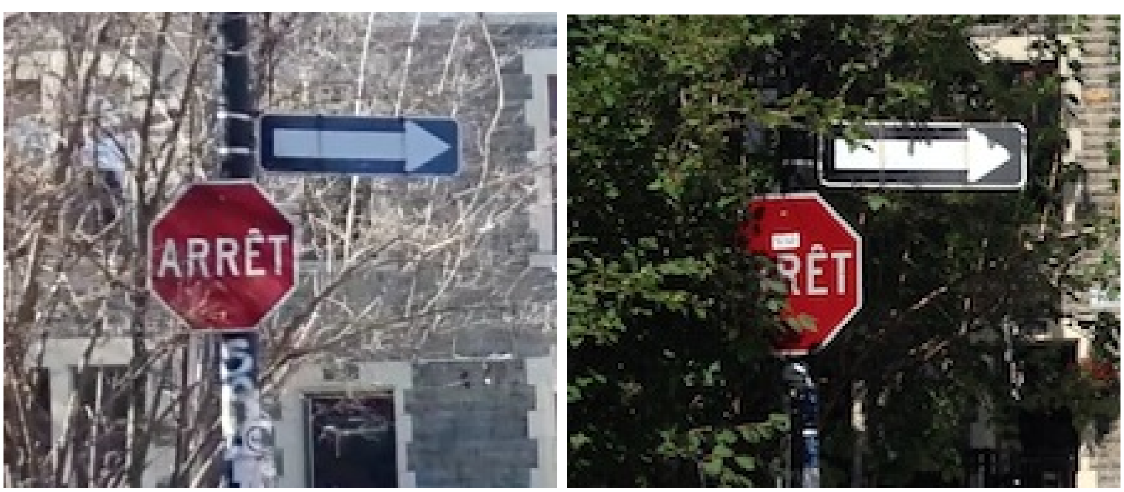


Figure 5.1 The Obstructed Stop Sign. The stop sign is visible in winter (left) and obstructed in summer (right).

5.2.1 Collaborative Sensing

One purpose of SafeCam is to provide the long term analysis on driver behaviors. The driving historical data does not only reflect the driver habits, but also aid to improve the online detection performance. In our experiment, stop signs are often invisible due to obstructions or unsatisfactory lighting conditions. For example, in Fig. 5.1, a stop sign is not detectable due to visually obstructed by an overgrowth tree during summer time (right figure captured in July). Meanwhile, during the winter time, SafeCam was able to detect the target stop sign because of the bare tree trunks. Thus, a crowdsourcing method collecting multi-user data from everyday use is desirable. Since SafeCam is able to automatically record the stop sign location information. Next time if the vehicle is approaching the same intersection, a driver will get alerts based on the historical data even if the vision-based detection is not working. Moreover, as the civilian GPS offers accuracy around 10 - 20 meters, a better speed estimation method [84] is needed to measure the distance between the vehicle and the intersectoin.

5.2.2 Eye Gaze Tracking

Moreover, another improvement we would like to make on SafeCam in the future is to monitor driver's gaze state and face direction in real-time combine with the driving behaviors monitoring [32, 182]. It is important to study the driver visual demand during different driving conditions, which could help us to detect driving distractions and avoid fatal road accidents [19, 183, 184] Such an advanced driver assistance system could also be used to investigate if the driver is aware of the crossing pedestrians, the road sign, the approaching traffic, etc [185]. We can use the information to analyze driver behaviors in different areas such as school zones, neighborhoods, as well as the parking lots. The study could promote safety to special pedestrians such as elders, children and seniors, as well as help driver to avoid hefty traffic fines.

5.2.3 Improve Gesture Spotting

Since human gestures (especially hand and arm gestures) are most commonly used for communication, reducing the chances of misclassifying static poses, by using continuous information. Gestures can be divided into two gestures, a communicative gesture (a key gesture or a meaningful gesture) and a non-communicative gesture (a garbage gesture or a transition gesture) [186–188]. The gesture segmentation or so called gesture spotting is the task of finding the start and end boundary points of a legitimate gesture.

Many gesture segmentation methods have been proposed, Lee and Kim [189] use the continuous video and use a threshold model corresponding to connecting patterns between key gestures. In addition, an early work [190] uses continuous dynamic programming (CDP) method to recognize seven different body gestures. In this method, a set of standard sequence patterns corresponding to key gestures were represented in the form of a spatio-temporal vector field, and compared with an input sequence using the CDP matching algorithm. While Barbic et. al. [191] focused on the gesture segmentation problem by proposing three methods, based on principal component analysis (PCA), probabilistic PCA, and the Gaussian mixture model (GMM). Although only key gestures are generally of interest, there are as many transition gestures in human motion.

Compare to the single threshold solution we used in SafeDrive, the neural network (NN) model [187, 192] has been proved that it is able to obtain hidden information from the training data and distinguish distracted gestures from non-gesture movements. It makes a combination of multiple thresholds for input features extracted from the smartwatch. We may build the NN model using Gyro data and determined the topology and optimal parameters offline. Then implement a functional module in the smartphone directly to spot driver gestures.

5.2.4 In-Vehicle Driving State Monitoring

We may combine SafeDrive with another work [2] to provide more comprehensive study on in-vehicle driver behaviors, such as how do you hold the wheel (holding position), are you smoking behind the wheel, as well make use of the microphone to capture audio samples for honk detection. A second potential application of smartwatch based driver monitoring is the fleet management market [193]. By using the sensors on smartphone and smartwatch, logistics fleet administrators may access real-time vehicle information and monitor driver activities in order to mitigate potential risks and reduce operational costs.

5.2.5 Communication Between Pedestrians and Vehicles

Better protection of pedestrians has been declared to be the top-priority (e.g., by the U.S. Department of Transportation [194, 195]). Pedestrians are more likely (1.5 times) to be killed than vehicle occupants in a car crash on each trip [196], as statistics have shown that traffic accidents involving pedestrians have become a major road safety concern [197].

There are many factors affecting pedestrian traffic safety, including the relative illumination of the traffic environment, pedestrian and driver behaviors, vehicle technology, vehicle and ambient sound levels, and other applicable factors. In addition, children or teenager are at even greater risk of injury or death from traffic crashes due to their small size, inability to judge distances and speeds, and lack of experience with traffic rules. Moreover, according to the analysis, electric vehicles have a 30% higher pedestrian traffic safety risk than internal combustion engine vehicles [198], because these vehicles have relatively silent engines compared to those of internal combustion engine vehicles, resulting in safety issues for pedestrians and cyclists due to the lack of engine noise to warn them of an oncoming electric or hybrid vehicle.

Though an extensive work has been done for pedestrian safety leveraging smart sensors and computer vision techniques [199–202], as well as the advanced technologies used in autonomous vehicles [203, 204]. However, the current systems are not perfect and we have seen through various incidents due to pedestrian detection failures (e.g., Uber self-driving car crash) [205,206]. This is a challenging task because of the difference in humans' postures, appearances. For example, there is a pedestrian walking/biking to an intersection, he/she may be blocked by other parking vehicles or buildings, the crossing cars may not be able to detect the him/her properly and result in crash.

Recently, Intelligent Transportation Systems provide technologies like the Dedicated Short-Range Communications (DSRC) for enhancing the driving safety and improving the quality of vehicular services [207–209]. By utilizing DSRC, Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications may have the potential to significantly reduce a large number of crashes through real time advisories alerting drivers to imminent hazards. Fox example, we may offer the system that using user's smartphone to communicate with Road-Side Units (RSUs) or vehicles to send broadcast alert/message when the risk of collision exists [210, 211]. It uses non-line-of-sight (NLOS) transmissions that could overcome the drawback we mentioned above, thus we will provide detailed study in the future. In addition, other systems like TrafficView [212] and StreetSmart [213] inform drivers through vehicular communication of the traffic conditions in their close proximity and can be further used to detect pedestrians on the road to prevent related accidents.

Appendix A

Contributions of Authors

This thesis is written by Landu Jiang (myself), which presents two driving safety projects SafeCam and SafeDrive under the supervision of Prof. Xue Liu.

The project 1 SafeCam [18] was published in Proceedings of the 2016 IEEE International Conference on Pervasive Computing and Communications (PerCom), the paper title "SafeCam: Analyzing intersection-related driver behaviors using multi-sensor smartphones". Professor Wenbo He and Dr. Xi Chen helped in data analysis and draft revision.

The project 2 SafeDrive [19] was published in Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT), the paper title is "SafeDrive: Detecting Distracted Driving Behaviors Using Wrist-Worn Devices". Mr. Xinye Lin and Mr. Chongguang Bi assisted in system development, experiment design and data analysis, Prof. Xue Liu and Prof. Guoliang Xing helped in draft revision.

Appendix B

Publications

Related publications are listed as follows:

1. Landu Jiang, Xinye Lin, Xue Liu, Chongguang Bi, and Guoliang Xing. 2018. "SafeDrive: Detecting Distracted Driving Behaviors Using Wrist-Worn Devices", Proc. ACM Interact. Mob. Wearable Ubiquitous Technol (IMWUT - UbiComp Journal). 1, 4, Article 144, January 2018.

2. Landu Jiang, Yu Hua, Chen Ma and Xue Liu. "SunChase: Energy-Efficient Route Planning for Solar-Powered EVs", International Conference on Distributed Computing Systems (ICDCS), 2017 IEEE.

3. Chongguang Bi, Jun Huang, Guoliang Xing, Landu Jiang, Xue Liu, and Minghua Chen. "SafeWatch: A Wearable Hand Motion Tracking System for Improving Driving Safety", In Internet-of-Things Design and Implementation (IoTDI), 2017 IEEE.

4. Landu Jiang, Xi Chen, and Wenbo He. "SafeCam: Analyzing intersection-related driver behaviors using multi-sensor smartphones", In Pervasive Computing and Communications (PerCom), 2016 IEEE International Conference on, pp. 1-9. IEEE, 2016.

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