Rear-end Collision Prevention Using Mobile Devices

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Abstract Portable devices like tablet PCs and smart phones are being used more often these days within the vehicular environment. Drivers use them for listening to music, navigation assistance, accessing internet and also mainly for speaking over the phone. Most of these features are made possible in the portable devices due to the availability and use of many sensors such as *global positioning system* (GPS), cameras, microphones, accelerometer sensors and gyroscope sensors. Although most of the sensors were designed for gaming or a better user experience, within a vehicular environment, they provide valuable information of the ego-vehicle and the surrounding environment. This paper probes into the possibility of using these sensors to measure vehicle dynamics, thus making a portable device a driving safety tool. We aim to design an *advanced driver assistance system* (ADAS) that warns drivers of potential rear-end collision scenarios. Toward this goal, this study focuses on front vehicle tail-light detection using the embedded camera of a portable device. This frontal vehicle tail-light detector is also used to estimate the distance between the ego- and front-vehicles based on the size of the detected tail-light. We propose a smart warning system using this information, together with the ego-vehicle dynamics computed using *inertial measurement units* (IMUs) (accelerometer and gyroscope). This system detects when the vehicle ahead brakes or intends to turn, and generates the warning signals when the speed of the ego-vehicle does not change accordingly.

Keywords
Taillight detection, driver assistance, computer vision

1. INTRODUCTION

Technological advancements have played an integral role in the development of the automotive industry. With the increasing use of in-vehicle infotainment systems, drivers tend to perform multiple tasks while driving. Since driver distractions is one of the main causes of accidents, it is important to develop active safety systems able to monitor the drivers behaviors, and detect intentions, preventing hazard situations. To improve the safety of the passengers, car manufactures are developing safer cars which are more pleasurable to drive. Some of the *advanced driver assistance systems* (ADASs) are adaptive cruise control, forward collision warning, anti-lock braking system, and collision mitigation by braking. These safety systems help the driver in maneuvering the car through the challenging surrounding environment.

Despite these efforts, the number of accidents still remain high in 2012 [9]. Singh [13] reported that 29% of the crashes were rear-end collisions, making it as one of the main contributing categories of all reported accidents. Some of the main causes for rear-end collisions are driver negligence in estimating forward vehicle maneuvers, lack of attention and low visibility. State-of-the-art ADASs uses RADAR or cameras to detect the proximity of the vehicle ahead, sending control signals when a possible crash is predicted. These systems are expensive and are mostly available in high-end luxury cars. This study probes into the possibility of detecting rear-end collisions with the sensors embedded in commercial portable devices.

Tablet and smart phones have sensors that can be used to measure useful vehicle dynamics information, thus making such portable devices an effective driving safety tool. Current portable devices including tablet PCs and smart phones come with a variety of useful sensors such as cameras, microphone, *global positioning system* (GPS), compass, accelerometer and gyroscope. Although these sensors are mainly used to provide better user experience for communication, social media and gaming, within a vehicular environment, they can provide valuable information of the ego-vehicle and the surrounding environment. *Inertial measurement unit* (IMU) sensors such as accelerometer and gyroscope give information about the ego-vehicle's lateral and longitudinal acceleration, yaw, pitch and roll. Compass and GPS give information of the bearing/ heading and current location. Through internet connectivity, information about current traffic and weather conditions can be obtained. Microphone gives valuable information about in-vehicular speech activity. Along with these sensors, most devices come with two cameras in opposite directions - one can be used to capture the driver's face and the other the road ahead.

This study focuses on front vehicle tail-light detection using the embedded camera of a portable device. Although the idea of brake light detection and warning the driver to avoid rear-end collision is not new [5, 8, 10, 11], the use of off-the-shelf portable devices for this task is relatively new. We use a Samsung Galaxy tab 10.1 which is mounted on the windshield of the car. Real-world driving data is collected and used to build the tail-light detector. Using the real-world driving recordings, we carefully annotate the tail-light of the front vehicle in selected video frames. We train a tail-light detector using the Viola-Jones algorithm based on Haar-like features. In controlled recordings, we achieve detection rates of 93.9 percent across all distance and 98.8 percent for distances over 8 meters. In real driving conditions, we achieve an average detection rate of 83.2 percent under different road and illumination conditions. In addition, we establish a mapping between the size of the detected tail-light image and the distance between the ego-vehicle and the detected car. The proposed system can be easily extended to detect front vehicle actions such as brakes or turn signals. The detection of such events is important in the design of warning systems to alert the driver to take appropriate prevention actions, especially when the distance between the ego- and front-vehicle is decreasing below an acceptable threshold.

Another important contribution of this study is the design of a smart warning system that considers the actions of the ego- and front-vehicles. The IMU and GPS sensors of the portable device are used to detect the driver's intentions (e.g., braking and turning), and vehicle information (e.g., speed). If the driver is aware that the forward vehicle is slowing down, and he/she takes the appropriate measures to reduce the ego-vehicle's speed to maintain a safe distance, the proposed system assumes that the driver is alert and does not produce any warning. The warning is signaled only when the driver's responses to the forward vehicle's actions are too slow or absent. In these cases, the system alerts the driver, preventing potential accidents. Due to the proliferation of portable devices, researchers are making more use of such systems for many applications. The greatest advantage of such system is its portability and that it is not tied to a particular car or manufacturer. Therefore, the proposed ADAS technology based on portable devices is not limited to high-end luxury vehicles but is available for any vehicle of any type.

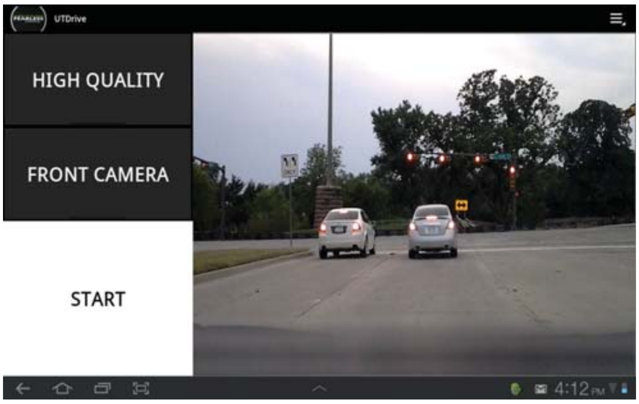

Fig. 1. Snapshot of the Android application.

Fig. 2. Setup of the Tablet mounted on the windshield. The setting is flexible and can be used in any car.

2. DATA COLLECTION

2.1. Portable Device

While we have used in our previous work a car platform equipped with multiple sensors [1, 2, 4, 6, 7], this project leverages the embedded sensors provided by a portable device to design an ADAS. We select a Samsung Galaxy Tab 10.1 WiFi as the portable device, which has the open Android operating system. We developed an Android app (program) to synchronously record all the relevant sensor information. Figure 1 shows the *graphical user interface* (GUI), which was designed to be a non-distractive tool, with big buttons to start and stop the synchronous data recording. At the beginning of the recording, the driver can select to use either the front and back camera with low or high quality. Along with these basic selections, the driver can also choose various settings under advanced options. These settings include the maximal duration of individual recording and the option to log additional information from the CAN-bus via bluetooth. More details on the Android app can be found at Sathyanarayana et al. [12].

We record the corpus with high quality setting, which provides 1280×720 videos at 30 frames per second. The tablet is mounted near the center of the windshield using a tablet holder as shown in Figure 2. This setting ensures the safety of the driver, minimizes the potential distractions caused by the tablet, and maintains consistency in data collection. The camera captures the road ahead. In addition to the video, we simultaneously record the inertial sensors, orientation and location information. Each recording begins before the vehicle starts moving and ends when the vehicle stops at the destination. The driver does not interact with the tablet while he/she is driving.

(a) Vehicle under bright illumination (b) Vehicle with poor illumination

Fig. 3. Example of frames from the data collection. The figures show changes in tail-light appearance under different illumination conditions.

2.2. Naturalistic Driving Data Collection

Over 30 hours of real-world driving data was collected under varying weather and illumination conditions. The main purpose of this data collection is to provide recordings which are used to build a robust tail-light detector, to infer the vehicle information (e.g., braking, speed), and to capture the driver responses in real-road traffic driving conditions. These recording also serves as testing data to evaluate the performance of the proposed system.

Building a robust tail-light detector requires the data collection to cover a wide range of cars' appearances. Despite the general features of vehicle tail-lights, their appearance can be very different depending on the type of vehicle, the design of the vehicle appearance, and the illumination conditions. For this reason, the data collection is conducted over multiple days, from different geographical locations, and at different times of the day. It also covers different road conditions including highway, city roads and residential areas. These variations in surrounding conditions also give rich data to study drivers' behaviors under natural driving scenarios. For example, this data gives insights about the distance maintained by individual drivers between the ego- and front-vehicle, the driver's response to road changes around the car, and the driver's reaction time measured by his braking and accelerating patterns. All these actions can be estimated with the data provided by the portable devices' sensors.

Figure 3 shows examples of the frames captured in this data collection. The figures show the shadows and changes in illumination, which are some of the challenges of naturalistic recordings. Notice that the same car appears in both frames.

2.3. Controlled Data Collection

In addition to the naturalistic driving recordings, we collected a controlled data with the portable device. The purpose of these recordings is twofold: to measure the performance of the system under ideal conditions (e.g., only one car in front of the ego-vehicle), and to establish an approximate mapping of the size of the detected tail-light image and the distance between the ego- and front-vehicles. The key for this data collection is that the distance between the ego- and front-vehicles is carefully measured.

Fig. 4. Illustration of controlled data collection.

We chose an empty parking lot to conduct the controlled data collection (see Fig. 4). The parking lot lines are used as reference landmarks to define the distance between cars. The ego-vehicle is parked with the mounted portable device. A second car is driven in a straight line in front of the ego-car. The recording starts with the two cars lined up in close proximity, and we move the front-car till the distance to the ego-car is 50 meters. The moving vehicle driver follows the instructions from an observer standing outside, who stops the vehicle every 2.75 meters (one parking space). This process is repeated 3 times to compensate for human errors, since drivers may not stop the at the exact point.

A total of three cars from different manufactures are chosen for this data collection. The cars include two sedans and one station wagon, with different color and size. The data collection is also conducted at different times of a day to include different illuminations. Figures 4 illustrates the process of the data collection. Each of the three vehicles is used as the front vehicle while one of the other two cars is used as the ego-vehicle. We collected nine sets of recordings (3 cars $\times$ 3 times). Although other sensors describing the vehicle signals are collected with the video, they are not used since the ego-vehicle is not in motion during the controlled data collection.

3. TAIL-LIGHT DETECTOR

The rear view of a vehicle consists of several distinctive parts that can be used for vehicle detection including the rear windshield, vehicle registration plate, tail-lights, and brake lights. This study focuses on tail-lights as the object-of-interest for vehicle detection. We select this approach since the appearance and relative location of tail-lights are sufficiently distinctive for vehicle detection. Also, they directly signal some of the actions of the front vehicle, such as braking, lane switching and turning.

(a) (b) (c) (d)

Fig. 5. Examples of tail-light areas used as object-of-interest (manually marked). Notice that the vehicle registration plate is consistently located between the tail-lights either at the same height as or below the tail-light locations.

Given the differences in the design of the vehicle and its tail-lights across different manufactures, we define our object-of-interest as the area of the vehicle that covers both tail-lights, brake lights and the vehicle registration plate (Fig. 5). As discussed in section 3.2, this area is big enough to detect cars even when the distance between the ego- and front-vehicle is 50 meters. We include the vehicle registration plate for two reasons. First, the plate is consistently located at the center of the car, either at the same height as or below the tail-light locations, as shown in Figure 5. Hence, it increases the appearance consistency of the object-of-interest. In addition, the vehicle registration plate is required by law to be placed in the rear of the vehicle in most of the countries so we expect to see it across all vehicles.

3.1. Viola-Jones' Tail-Light Detector

We used the Viola-Jones object detection framework to build the vehicle tail-light detector. This framework has been widely used for human face detection [15]. It is known for its fast cascade implementation in which false negative images are quickly ignored. Therefore, this algorithm is ideal for vehicle tail-light detection in real-time applications (the evaluation presented in this paper is implemented with offline algorithms). The Viola-Jones object detection method uses a cascade architecture of weak AdaBoost classifiers. The classifiers are trained with Haar-like features that describe the shape, relative position and orientation of the object-of-interest. In each stage, the features are used to train a classifier that rejects more non-object patterns than the previous stage, while maintaining high detection rate for the object-of-interests.

The Voila-Jones framework requires positive images containing the object-of-interest (tail-light area in this study) and negative images containing other objects. We manually choose both positive and negative images from the videos recorded in our naturalistic driving data collection (Sec. 2.2). For positive images, the tail-light regions are manually marked with a rectangular box following the definition of the tail-light object. During the process, we ignore cases where the tail-light

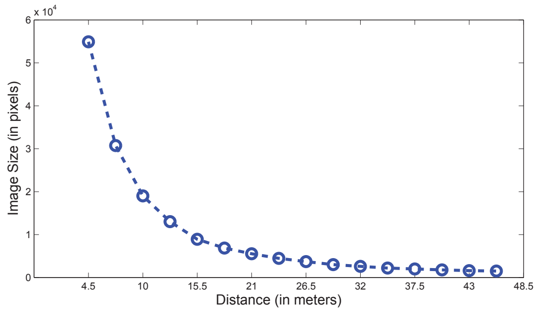

Fig. 6. Mapping between the average number of pixels of the detected car and the distance between the ego- and front-cars.

object is too small to be perceived by human eyes. Figure 5 shows examples of positive images. In total, we extract 1460 positive images from the real-world driving data. From these images, we marked 3000 tail-light objects, since most of the positive images have multiple front vehicles in different lanes. The negative images are selected from frames without any front vehicles. We use 3496 negative images, which include 3019 general negative images and 477 specific negative images. We build the tail-light detector using the implementation of the Viola-Jones algorithm included in the *open computer vision library* (OpenCV) [3].

3.2. Front Vehicle Distance Estimation

While the main goal of the tail-light detector is to find the cars in front of the ego-vehicle, the outputs of the tail-light detector are also used to approximate the distance between the front- and ego-vehicles. The estimation relies on the premise that the size of the detected tail-light object is closely related to the distance between the front car and the portable device. As the distance increases, the image of the car captured by the camera decreases. We use the data collected in controlled conditions (Sec. 2.3) to estimate the mapping between the detected tail-light size and the distance between the front- and ego-vehicles. This mapping only approximates the actual distance since cars have different sizes.

We apply the tail-light detector on the video frames captured when the front vehicle stops. Notice that the ego-vehicle is not moving during the controlled recording (Sec. 2.3). We estimate the number of pixels associated with the detected tail-light object. Due to the high similarity between consecutive frames, only five frames with 0.333s (10 frames) interval are considered each time the front vehicle stops. Therefore, we extract 45 video frames associated with each predetermined location (3 cars $\times$ 3 times $\times$ 5 frames = 45 frames). We use the average number of pixels of the 45 detected tail-light objects as the mapping size.

Figure 6 shows the mapping between the average number of pixels and the distance between the ego- and front-cars.

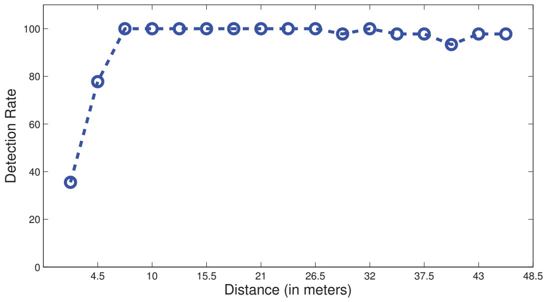

Fig. 7. The performance of the tail-light detector for different distances in controlled recordings.

The figure shows that the image size decreases exponentially with the distance. We use this mapping to estimate the performance of the system in naturalistic driving recordings for different distances (see Sec. 3.3).

3.3. Performance of the Tail-Light Detector

First, we evaluate the performance of the tail-light detector in the controlled driving recordings. Figure 7 shows the tail-light detection rate at each measured distance. These metrics are estimated by comparing the output of the tail-light detector with manual annotations. The performance of the system is above 98.8 percent when the distance is between 8-50 meters. Notice that when the distance between the front- and ego-vehicles is too close (i.e., <2 meters), the tablet fails to capture the complete view of the front vehicle. Therefore, the tail-light detector fails to recognize the front vehicle. This type of miss detection can be reduced if a tracking method is applied. Since vehicles at further distances can be accurately detected, their locations can be estimated with the tracking algorithm when the detector fails to detect the near distance vehicles. In addition, when combined with the overall system, the warning signals should be generated before the vehicles get this close.

The second evaluation of our tail-light detector is conducted in naturalistic driving conditions (Sec. 2.2). We select real-world recordings that were not used for training the detectors. Following the same manual annotation process, as described

(a) Tail-light detector output (b) Manual annotation

Fig. 8. Examples of results of the tail-light detector.

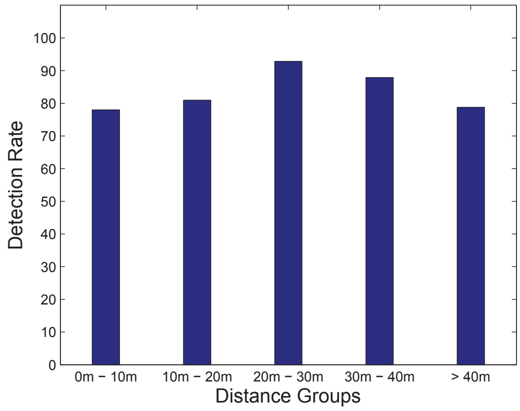

Fig. 9. Detection rate of the tail-light detector in each of the 5 distance groups.

in Section 3.1, we marked 445 tail-light objects identified in 186 randomly extracted frames from the testing recordings. The tail-light detector is applied to these images, and the detection results are compared with the manual annotation. Figure 8 shows the results for one frame, in which the front cars are correctly detected.

We expect that the performance of the tail-light detector will vary according to the distance that separates the ego- and front-vehicles. Since the data corresponds to naturalistic driving recordings, we do not have the actual distances. Therefore, we use the mapping results from Section 3.2 to cluster the annotated tail-light objects into five groups according to their size: less than 10 meters, between 10 and 20 meters, between 20 and 30 meters, between 30 and 40 meters, and greater than 40 meters. We acknowledge that these are approximated clusters. In the testing set, there are at least 45 tail-light objects in each group.

Figures 9 shows the detection rate in each of the five groups. Overall, the average detection rate across all groups is 83.2 percent. The highest detection rate is achieved in the range between 20 and 30 meters, which reaches 93 percent. The lowest detection rate is for vehicles that are closer than 10 meters (78 percent). This result agrees with the performance observed in controlled conditions (see Fig. 7). As expected, the performance drops as the distance increases since the tail-light size becomes too small to be recognized. These promising results suggest that the tail-light detector can be used to detect and track the front vehicle in real-world driving scenarios.

To improve the performance of the system, it is important to understand the reasons that make the tail-light detector fails. We observe that the missed detections in the near distance group are mainly due to the blinking turning indicator or adverse illumination conditions. Figures 10 and 11 show examples of these cases, respectively. interestingly, the effect

(a) Detection result (b) Manual annotation

Fig. 10. Missed detection due to turning indicator.

(a) Detection result (b) Manual annotation

Fig. 11. Missed detection due to adverse illumination.

of these conditions is not as detrimental for cars far from the ego-vehicle.

While the tail-lights of vehicles are usually red and can be easily distinguished from the car's color, there are cases in which the vehicle and its tail-lights have similar color. Figure 12 illustrates an example of this case. The tail-light detector fails to detect these cars. We believe that this problem can be overcome by increasing the number of training images spanning these challenging cases.

4. REAR-END COLLISION PREVENTION SYSTEM

This study proposes a smart warning system based on a portable device that integrates the tail-light detector results with the knowledge of the ego-vehicle activity (i.e., braking, turning, accelerating). The vehicle activity is estimated though IMUs (accelerometer and gyroscope) and GPS. The novelty in our approach is the use of existing sensor information from portable devices, which is combined with the distance mapping results and tail-light detector to improve the efficiency of the entire system. The resulting collision prevention system is an affordable ADAS that can be used in any vehicle. With a high

(a) Detection result (b) Manual annotation

Fig. 12. Missed detection due to similar appearance between tail-light and the vehicle itself.

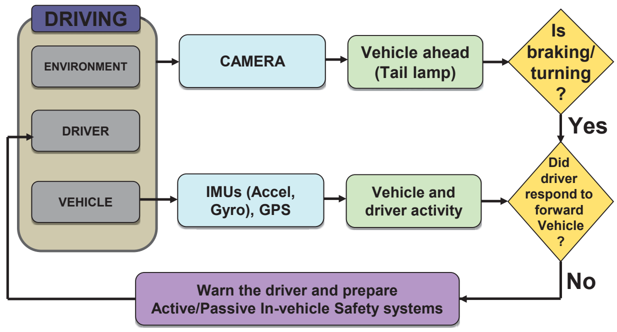

Fig. 13. System overview showing the decision fusion of two separate systems that detect tail-light of front vehicles and monitor the driver activity.

accuracy of over 90 percent in detecting tail-lights of front vehicles at a considerable distance (20-30 meters), we adopt a sensor fusion approach to track the driver's responses to the activity of the front cars.

Figure 13 gives the overview of the proposed rear-end collision prevention system. The two key results from the tail-light detector, as described in Section 3, are the detection of the vehicles ahead and their distances from- the ego-vehicles. Based on the distance and location of the front vehicles, we can estimate if they are getting closer of farther from- the ego-vehicle. From the camera and the described image processing steps, the system raises a warning flag (Yes) whenever the driver ahead is braking and the distance between the front- and ego-vehicles decreases below a given threshold.

The ego-vehicle's movements are captured and evaluated from the IMUs (accelerometer and gyroscope) and GPS of the portable device. The portable device mounting orientation is manually aligned along the vehicle's axis to avoid any alignment mismatch. Although there are various methods which have been proposed for mounting orientation correction [14], it is observed that there is minimal error due to manual alignment. Therefore, this study neglects this correction. Longitudinal movements of the ego-vehicle is of primary importance in this study. The longitudinal movements involve vehicle speed and acceleration/deceleration. GPS gives a coarse approximation of the vehicle speed. The accelerometer data gives more precise readings but it is very sensitive to vehicle vibrations. The high frequency noise in the accelerometer is attributed to small changes and vehicle vibrations. Since the rear-end collision prevention system should warn the drivers as quickly as possible, we use both the GPS and the accelerometer data. We extract the longitudinal acceleration by low pass filtering the accelerometer data, and by extracting the effect of gravity, which is implemented by compensating for drifts using the gyroscope data. Figures 14 illustrates this longitudinal acceleration, and the corresponding normalized

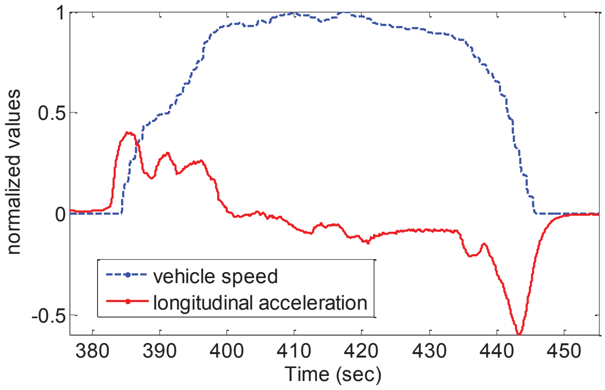

Fig. 14. Vehicle speed and longitudinal acceleration of the vehicle estimated from the sensors of the portable device.

vehicle speed for a segment of the route. This information gives insights about the ego-vehicle's driver intent including whether he/she is braking or accelerating. It also provides an estimation of the vehicle speech which is important to evaluate whether the distance between the ego- and front-car is enough for safe driving. Notice that our previous work [12] showed that sensor information from portable devices can be used to extract comparable vehicle dynamics information than the ones extracted from CAN-bus signals such as steering wheel angle and vehicle speed. It was also shown that the sensor information from portable device achieves better accuracy in maneuver recognition than the ones obtained from basic CAN-bus signals.

The proposed rear-end collision prevention system fuses these two separate systems that estimate the front- and ego-vehicle activities using the sensors of the portable device. We compute a decision level fusion to evaluate whether the driver is aware of the surrounding road conditions. The approach is a simple decision tree that assesses if the front vehicles are braking, and if the distance between the cars is reducing. If the speed of the ego-car decreases accordingly, the system understands that the driver is taking the appropriate actions, and does not send any alarm. If the speed of the car does not decrease, the system alerts the driver so that he/she can cope with the hazard situation.

5. CONCLUSIONS

This study proposed a framework that uses the sensor information from portable tablets or smart mobile phones to prevent rear-end collisions. The focus of this study was on building a front vehicle tail-light detection and using its output results to design a rear-end collision prevention system. The tail-light detector is built using the Viola-Jones algorithm, achieving a detection rate of 93.9 and 83.2 percents in controlled and naturalistic driving recordings. We estimated a mapping between the detected tail-light size and the distance between the front- and ego-vehicles. This mapping allowed us to estimate the performance of the tail-light detector as function of distance in naturalistic driving recordings. This mapping was leveraged by the rear-end collision prevention system to estimate the approximated distance of the detected cars. The IMUs and GPS sensors were used to estimate the information about the ego-vehicle (braking, speed, accelerating). The proposed ADAS fused all the information about front- and ego-vehicle dynamics to warn the driver about potential hazard scenarios.

There are many interesting directions that we are considering to improve the proposed rear-end collision prevention system. Once the system sends a warning, the approach can trigger other active/passive safety systems for precautionary actions. It can also trigger a warning signal using any available medium, including tactile, haptic, acoustic or visual modalities. The proposed system is flexible and capable of running in real-time. Its modular architecture gives the opportunity to separately improve each of the blocks. The proposed system is affordable and can be employed in any car, since it is implemented on a commercial portable device.

In our future work, we will also explore techniques to improve the performance of the tail-light detector by considering temporal information. For example, we can couple the tail-light detection with tracking algorithms. In addition, we will focus on detecting the front-vehicle actions such as braking and turning. Once the tail-light area is detected, we will track changes in color across consecutive frames in the detected regions. This approach will allow us to identify braking and turning signals which will provide valuable information. Likewise, we will collect more naturalistic recordings to improve the performance of the detection system. In particular, we will consider recordings at nighttime, which will provide very different tail-light appearance. The aforementioned directions aim to design a ADAS based on a portable device that is robust and accurate regardless of the road conditions, which is our longterm goal.

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