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Vehicle Detection Techniques for Collision Avoidance Systems: A Review

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Abstract:

Over the past decade, vision-based vehicle detection techniques for road safety improvement have gained an increasing amount of attention. Unfortunately, the techniques suffer from robustness due to huge variability in vehicle shape (particularly for motorcycles),cluttered environment, various illumination conditions, and driving behavior. In this paper, we provide a comprehensive survey in a systematic approach about the state-of-the-art on-road vision-based vehicle detection and tracking systems for collision avoidance systems(CASs).This paper is structured based on a vehicle detection processes starting from sensor selection to vehicle detection and tracking. Techniques in each process/step are reviewed and analyzed individually. Two main contributions in this paper are the following: survey on motorcycle detection techniques and the sensor comparison in terms of cost and range parameters. Finally, the survey provides an optimal choice with a low cost and reliable CAS design in vehicleindustries.

Keywords—Driver assistance system (DAS), motorcycle detection, sensors, tracking, vehicledetection.

1. INTRODUCTION

Each year approximately 1.24 million people around the world die on roads and between 20 and 50 million with-stand non-fatal injuries [1]. If the current trend continues, road accidents are predicted to increase by 65% and become the fifth major cause of death by 2030 [2]. In economic terms, the direct costs due to road accident injuries have been estimated at US$518 billion, which is about 1% of gross national product (GNP) of low-income countries, 1.5% inmiddle incomeand2% in high motorized countries [3]. This high fatality rate and economic costs have prompted the United Nation(UN)tolaunch a global program—"Decade of Action for RoadSafety2011–2020" in May 2011 [4].

Driver inattention, fatigue and immature behavior are the mainfactorscausingroadaccidents.AccordingtotheNational Highway Traffic Safety Administration (NHTSA) that nearly 25% of police-reported crashes implicate some kind of driver inattention—the driver is distracted, fatigued, asleep or"lost in thought" [5]. Almost 50% of the accidents which involve inattentiveness are due to driver distraction [5], [6]. Thirteen kinds of possibly distracting activities are [7]:

drinking or eating, outdoor people, event or object, talking or listening on mobile phone and using in-vehicle-technologies etc. Since distraction can be caused in several ways, NHTSA categorizes it into following four types[5]:

- Visual distraction (e.g., looking away from theroadway)
- Cognitive distraction (e.g., being lost inthought)
- Auditory distraction (e.g., responding to a ringing cell phone)
- Biomechanical distraction (e.g., manually adjusting the radiovolume)

Fatigue is the second main factor and causes almost 25%– 30% of road crashes [8]. Among these, mental fatigue and central nervous fatigue are the most hazardous types while driving, as these will ultimately result in drowsiness, increas- ing the possibility of an accident. Four common types of fatigue are:

- Localphysicalfatigue(e.g.,inskeletalorocularmuscle)
- Generalphysicalfatigue(followingheavymanuallabor)
- Central nervous fatigue(sleepiness)
- Mental fatigue (not having the energy to doanything)

Immature driving behavior is also a main factor to cause road accidents,e.g.,shortcutmaneuversthatposegreatthreatto opposingvehicles,ignoranceoftrafficsignalsduringlate-night or early morning. This is particularly serious to the vulnerable road users including motorcyclists, bicyclists and pedestrian, accidents related to motorcyclists have highest percentage be- cause of less protection and high speed [9]. The accident rates are particularly higher in ASEAN region than other countries [9]. An unexpected obstacle or a slip of the wheel can easily cause motorcyclist to lose control resulting in a road crash. Other reasonsinclude:

- Lane splitting, i.e., driving between twolanes
- Ignoring traffic signs and roadconditions
- Violating speedlimits
- Driving on the wrong side ofroad
- Not using indicators atturns
- Driving while under the effect ofdrugs
- Vehicle (or motorcycle)faults
- Deliberate aggressiveactions

Otherthanhumanerrors,roadandenvironmentalconditions canalsocausetrafficaccidents.Thelatterincludesinsufficiency of street lights and climatic conditions, e.g., foggy and rainy weather reduces the visibility and makes roads slippery. The former may include the places where there are sharp turns, intersections or junctions. Roughly one-third of accidents take place at intersections [10].

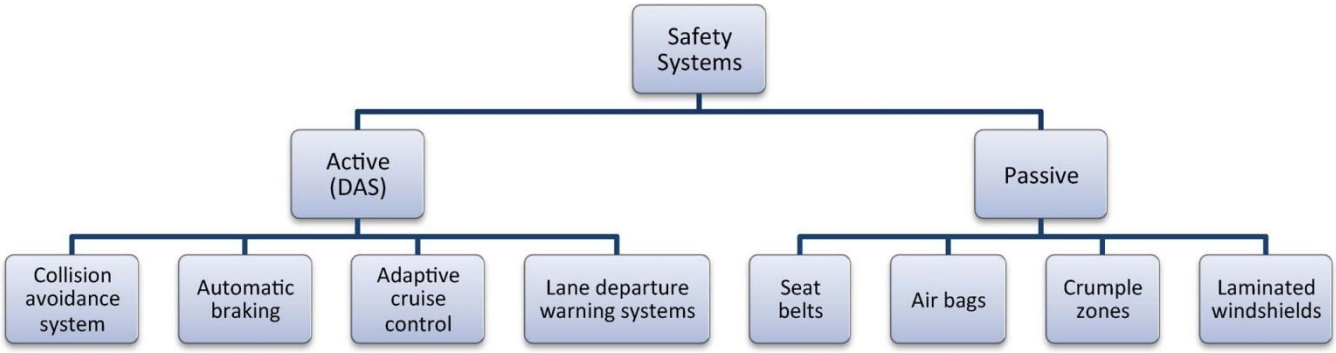

Fig. 1. Vehicle safety systems and their types.

Since human behavior is the main cause for occurrence of accidents(whereerearendcollisionsarethemostcommonform [10]), it is critical to equip with safety systems in vehicles as shown in Fig. 1. The safety systems can be either active or passive.Thelattersuchasseatbelts,airbagsandcrumplezones have been widely employed for many years and it has almost reached its full potential in reducing the number of casualties [11]. The former also known as on-board automotive driver alert system or driver assistance systems (DAS) including col- lision avoidance systems, brake assistance and lane departure warning systems takes proactive steps to prevent an accident before ithappens.

In this paper, we provide a review of sensors and techniques for vehicle detection and tracking for CAS, which is an auto- mobile safety system designed to reduce the possibility of an accident. It is also recommend to read other comprehensive reviews[12]and[13]fordriversafetysystems.Thefirstreview [12], provides a detailed review on on-road vehicle detection and tracking using optical sensors until 2005. The latter [13], is an up-to-date and thorough survey of vision-based vehicle detection,trackingandbehavioranalysis.Thispaperisdifferent from [13] due to addition of survey on sensors (active and pas- sive), their comparison and literature for motorcycle detection techniques.We focusonfullsystemi.e.,hardwareandsoftware solution for CAS while [13] addresses the driver behavior analysisandtechniquesforvehicledetectionwithminordetails on sensors. CAS should notify the driver with the information about number and type of vehicles in close proximity, their distance and relative velocities. To extract this information, it may use different sensors (radar, laser and camera) to acquire on-road traffic data followed by detection and classification of vehicles. Once an imminent crash is anticipated, these systems either provide a warning to the driver or take action autonomously without any driver input (by braking or steering orboth).

(a) (b)

Fig. 2. (a) Portable laser scanner with a weight of 900 g, produced by IBEO;
(b) Laser scanner with a range of 250 m and 360° coverage manufactured by SICK [17].

In recent years, many commercially viable products related to CAS have been developed and equipped in the auto com- panies such as Volvo, Ford, Honda, Subaru, Mercedes-Benz, Toyota, and Nissan [14]. Some third parties, e.g., SmartEye andSeeingMachines,offercamera-basednonintrusivedevices for CAS development such as Volvo cars [15], [16], where fusionofcameraandradarispracticed[15].TheGermancom- pany IBEO and its parent company SICK developed various laser scanners for road users to address different applications, range of operation and cost. For example, the IBEO LUX scanner shown in Fig. 2(a) has small size (85cmX128cmX83cm)andlightweight(900g);theLD-LRS2100displayedin Fig.2(b)hasarangeof250m,acoverageof360°,anda0.125°resolution [17].

The existing products have shown their effectiveness to the road safety, but they still suffer from issues in hardware such assensorquality(opticalsensors)andsoftwareincludingalgo- rithm development [12], [18]. The former should meet the fol- lowing factors: robustness (under various weather conditions), real-timedatascan,andcostefficientsolution.Thelattershould befastandaccurateenoughtotakeinitialactioninCAS.There is tradeoff between the factors, i.e., more robust and accurate the products are, the higher price/cost may be. Unfortunately, forcommercialproductsthecostisacriticalissuetothevehicle consumers, i.e., if are they willing to pay more prices for the products?WefocusonvisionbasedsystemsfordesigningCAS due to low cost and small size of optical sensors. A survey on sensors is presented for comparative analysis of optical sensors versus other sensors to justify our choice forvision based CAS. The aim is to find a combination of sensor anddetection algorithm for an optimal CAS design. We argue that more focus should be placed on algorithmic side as progressin computational hardware is drastic following the Moore's law [19]. Admittedly, the algorithmic design still lack of

(i)best features for shape matching,

(ii) classifier selection for recognition,

(iii) a large database for classifier training, and

(iv)fast and accurate tracker. This paper will discuss these issues.

CAS are rapidly making their way into the new vehicle fleet and major automobile manufacturers have made numerouspredictions for the development of CAS technology in the near future. This compels us to survey CAS techniques with theirpros and cons which may help in designing a reliable CAS. The ultimate objective of this paper is to identify appropriate sensor(s), motion or appearance clue(s), classifier and/or tracker for a real time CAS design which can perform robustly fordifferent scenarios (day, night, rain, fog etc.).

2. SENSORS FOR CAS

Although the focus of this paper lies in vision-based vehicle detection, it is pertinent to include a brief treatment ofcomplimentary modalities currently used in on-road vehicle detection. Sensors in CAS collect information about the roadconditions and can be classified into two main categories: active and passive. The former emit signals and sense the reflectionsignal to identify targets/obstacles. That the latter acquire data in nonintrusive manner, such as optical sensors or cameras [20].

2.1 ACTIVE SENSORS

The most common approaches to detect vehicles by active sensors include Radar-based [21], [22], and Laser or Lidar(Light Detection and Ranging) based [23], [24]. Pulse Doppler Radar framework [21] was used to detect andthen track obstacles in front of vehicle. It was mounted in the front lower part (see Fig. 3) of an ego vehicle. The systemcalculated the distance between ego vehicle and target, and the relative speed by observing echoes of Radar signals. Thesystem also worked well under various weather conditions and showed positive results (distance) for 150 m. A compressedsensing radar detection scheme based on sparsity of the cyclic autocorrelation was proposed in [25] for approaching vehicledetection, but only the simulation results were provided. Radar based driver safety systems were proved successfully in realtime multiple lane vehicle detection by using discrete time sig-nal processing [26]. Vehicles speed detection reached 90% ofaccuracy with 200 classification tests. The system also worked well in different scenarios such as low illumination conditions(fog, rain etc).

Fig. 3. Radar system mounted on the front end [21].

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(a) (b)

Fig. 4. (a) Laser scanner with a range of 80 m, 180◦ coverage, and resolution of 0.25◦

(b) The same scanner mounted in front of an instrumented test vehicle [17].

Laser and lidar based systems transmit and receive ultraviolet, visible, and infrared waves of electromagnetic spectrum.The waves that come back to the receiver are collected with a telescope and counted as a function of time. Using the speedof light, we can calculate how far the photons have traveled round trip. Typical 1D and 2D lidar sensors are inexpensive inproduction and easier in packing than radar. A laser scanner is an extended version of a laser range finder, which adoptsthe time-of-flight principle to calculate the distance to an object. The authors in [23] developed an approach to detectand classify multiple vehicles by a Laser scanner mounted on a vehicle.

The classification was based on different criteria:

sensor specifications, occlusion reasoning, geometrical configuration, and tracking information. The estimated confidencelevel was computed accounting the geometrical configuration, the classification, and the tracking time. The system was thentested under several conditions (highways, urban centers) with three different Laser scanners for better accuracy. Modern laserscanners, such as SICK can collect high spatial resolution data with high scanning speeds and proved their usefulness for200 miles test run conducted by United States Department of Defense Advanced Research Projects Agency (DARPA) [17].

(a) (b)

Fig 5(a) 3D Lidar Sensor HDL-64E

(b) The Same Scanner Mounted on the top of Toyota Priuse.

More recently, Velodyne has designed small size 3D lidar sensor HDL-64E for obstacle detection and navigation of autonomous ground vehicles. It uses 64 fixed-mounted lasers to measure the surrounding environment, each mechanically mounted to a specific vertical angle, with the entire unit spinning. This approach dramatically increases reliability, field of view and point cloud density. With its full 360◦ horizontal field of view by 26.8◦ vertical field of view, 5–15 Hz user-selectableframe rate and over 1.3 million points per second output rate, the HDL-64E provides all the required distancing sensing data.This device has been chosen for Google's fleet of robotic Toyota Priuses as a project to design an autonomous self-driving car[27]. Fig. 5 shows a HDL-64E sensor and its employment in Google autonomous car.

2.2 PASSIVE SENSORS:

Passive sensors collect information by receiving the signals without emitting them and include acoustic [28]–[30] and optical (camera) sensors [31]–[40]. Recently, a sensing technique for real time detecting and tracking an approaching vehiclebased on acoustic cue has been proposed [30]. First, it extracted a robust spatial feature from noisy acoustical observationsby employing gradient method. Then, the spatial feature is filtered out through sequential state estimation using particlefilter. The proposed system was tested with real world acoustic data, which was obtained by the vehicle-mounted microphonesoutside the cruising vehicle. Authors in [29] presented a comprehensive design of an acoustic sensing hardware prototype todetect vehicles by estimating congestion on the road using the negative feature (noise) of urban road environment. It sampledand processed road noise to calculate several metrics such as vehicle speed distribution and vehicular honks, with speedsestimated from honks using differential Doppler shift. The metrics were then transferred to a remote server over Generalpacket radio service (GPRS) every minute. Based on these metric values, server (a remote processor) determined the trafficcondition on the road. Moreover, motorcycles were detected using three unidirectional microphones in a microphone arraythrough its unique low frequency signal components [28].

Optical sensors/vision-based CAS are utilized to track approaching and preceding vehicles more effectively than activesensors as visual information can provide a brief description of the surrounding vehicles [31]–[33]. Detection may be carriedout by using stereo camera [41], single [35], [36] or multiple cameras [37], [38]. The cameras can be mounted either on theinner side of wind screen near the back view mirror or on the rear side of body of vehicles. In many cases, multiple camerasmay be required to obtain full 360◦ view of the surrounding environment. To perform night time detection infrared (IR)cameras were needed instead of ordinary cameras due to their poor vision under low brightness conditions [39], [40].The use of both monocular and stereo-vision cues typically manifests itself in the use of monocular vision for detectionand stereo vision for 3-D localization and tracking. Lim et al. [42] detected vehicles using a classifier on the monocular plane,estimated the ground surface using disparity map and tracked with extended Kalman filtering in the stereo-vision domain.Track management for reduction of false alarms and improved precision was also presented. In a similar approach [43], a setof AdaBoost detectors were trained for multiple vehicle views and candidate regions were verified by looking for peaks inthe disparity range. Monocular vision had the advantage

of detecting two objects which lie close to each other in 3D spaceand cause a typical miss in case of stereo-vision approach [44]. Monocular vision and stereo vision were also utilizedto work in cascade where the former was used to generate vehicle candidate regions, and the latter to verify those regionsas vehicles, by searching for vertical objects in the 3-D domain [45]. Table I summarizes the existing active and passive sensorsin terms of strengths and weaknesses.

2.3 FUSION OF SENSORS:

Multiple sensor approaches are more likely to progress and yield more reliable and secure systems as compared with a single sensor [46], [47]. In fusion, either sensors perform detection simultaneously and then validate each other's results or onesensor detects while the other validates .

Table 1 :Summary of various Sensors for CAS

Sensor Type	Specific Sensor	Distance	Cost	Advantages	Disadvantages
Acoustic [30]	SONY ECM-77B	Depends on sound waves amplitude and mic sensitivity	≈ 350 USD	• Omni-directional microphone • An economical solution • Real time	• Interference problem • Noise sensitive • Short range
Radar [21, 22, 25, 26]	Delphi Adaptive Cruise Control	175 m	2,000 USD	• Measure distance directly with less computing resources • Longer detection range than acoustic and optical sensor • Robust in foggy or rainy day, and during night time.	• Interference problem • Higher cost than Acoustic • Classification issue • More Power consumption than acoustic and optical sensor
Laser/Lidar [23, 24]	Velodyne HDL-64E Laser Rangefinder (3D LIDAR)	120 m	75,000 USD	• Longer detection range than acoustic and optical sensor • Independent of weather conditions • Modern lidar/laser scanners acquire high resolution and 3D information	• Road infrastructure dependency • More Power consumption than other sensors • High speed 3D scanners are expensive
	SICK LMS511-10100 (2D)	80 m	7,000 USD		
Optical (camera) [31-40]	SV-625B	100m for day 12m for night (Depth of focus)	160 USD	• Low cost, easier to install and maintain • Higher resolution and wider view angle • Extensive information in images • Independent of any modifications to the road infrastructure. • Accumulate data in nonintrusive way	• Image quality depends on lighting and weather conditions • Requires more computing resources to process the images
Fusion of Sensors [48-73]	Not Applicable	Depends on sensors fused	Depends on sensors fused	• Increases system robustness and reliability • Broadens the sensing capabilities • Collect maximum information of surroundings	• Separate algorithms for each sensor • Expensive

2.4 RADAR AND VISION:

Radar-vision fusion for on-road vehicle detection and perception has received more attention inrecent years [50]–[65]. In this fusion, radar is mainly used for estimating regions of interest (ROIs) or distance, while recognition is carried out pattern recognition algorithms. Guardrails locations were determined by radar data and vertical symmetryfeature of the limited region in images (ROI) detected vehicles [51]. In similar approaches [59], [60], vehicles were detectedusing symmetry, edge information and optical flow features of images. Kalman filtering on radar data was employed fortracking and ranging of identified vehicles. Classifier based detection using HOG, Haar and Gabor features, and rangefinding by radar was successful in [57], [61]. In another study [58], the input image was analyzed for salient locations usinga variety of visual features including orientation,

intensity, color, and motion. Once the vehicle became known, its distancewas calculated from radar and vision fused data. Monocular vision was used to solve structure from motion, with radarproviding probabilities for objects and the ground surface [62]. The authors in [56] used vision operations on the inverse perspective mapped image and ranged via radar. Camera and radar detections were projected into a common global occupancygrid, vehicles were tracked with Kalman filtering in a global frame of reference [52]. In [63], a radar-vision online learningframework was utilized for vehicle detection.

2.5 LIDAR AND VISION:

Lidar and Vision: Fusion of lidar with monocular vision has been explored in recent years [47]. Initially using lidar data,detection and tracking were performed to obtain more reliable object detection whereas the information from camera and lidarwas simultaneously accessed for classification. Stereo vision system (SVS) was applied to verify the actual existence of potential obstacles assumed by multi-layer lidar in [49]. The authors in [66] developed a multiple sensor approachusing Radar, vision and lidar technologies with widely overlap ping fields of view. Two independent Laser scanners and severaloverlapping short range Radar sensors were mounted on the sides of car, and front was covered by three powerful long-rangesensors (i.e., stereo-vision, radar, and laser). By considering confidence and reliability measures for all sensors, the obstaclemap estimated by sensor fusion was revealed to be more reliable and precise than any of individual sensor outputs.

2.6 ACOUSTIC AND VISION:

Acoustic and Vision: Chellappa et al. [67] took advantage of complementary information obtained by fusing acoustic andvideo sensors for detection and tracking. In detection phase, acoustic data was processed to estimate the direction-of-arrival(DOA) of target which defines the approximate target location in video.

2.7 RADAR AND LIDAR :

Radar and Lidar: System based on collective information acquired by Radar and Lidar developed in [68] produced salientobstacle features associated with the front bumper of experimental vehicle. The state was estimated with Bayesian methods(Extended Kalman filter or Particle filters) and tracking results by two independent systems were fused for improved detectionand tracking.

2.8 OTHER MULTIPLE MODALITIES :

Other Multiple Modalities: Recently, the authors in [28] applied fusion of Radar, sound sensor, stereo and IR camerato detect and monitor the motorcycle motion. The system was mounted on one nearby pole and more robustness and reliabilitywere achieved. A safety system was presented in [69] where a test vehicle (Fig. 6 provided by Audi was equipped withtwo high-resolution video cameras, one time of flight laser. scanners, two short-range radars, one long-range radar, eight ultrasonic sensors and one differential global positioning system (DGPS). A contextual resource allocation scheme was applied for the development of a driver assistance system to estimate the time to collision and assess the severity of impact

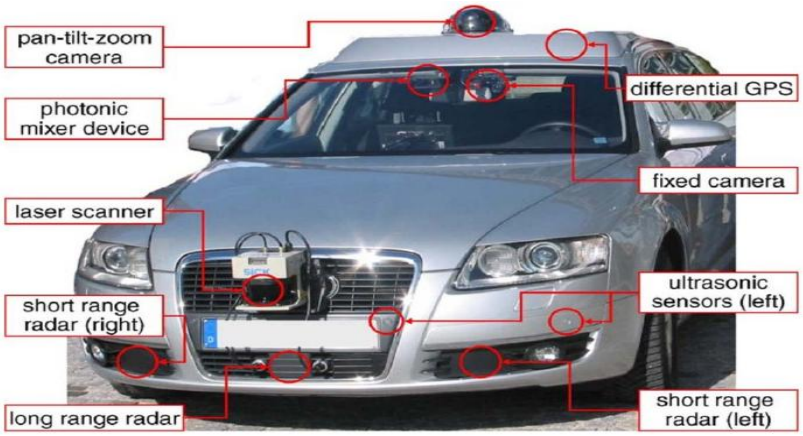

Fig 6: Test Vehicle used to acquire road traffic Scenes for evaluation

3. DISCUSSION :

On-road vehicle detection has always been the major focus in vehicle industries. The introduction to CAS in moderncars may reduce the accidents rate by quickly and robustly identifying all sorts of vehicles and warning drivers aboutpotential accident threat. However, it is challenging for vehicle identification due to huge variability in shape, color, and size ofvehicles. Cluttered outdoor environment, illumination changes, random interaction between traffic participants, and crowdedurban traffic system make the scenario much more complex.

Development of CAS faces two main challenges: real-time and robustness. The processing time in former is indirectly relatedto vehicle speed. Higher the speed of vehicle less the time is available for processing a frame. Robustness must be fulfilled ifthe ego car is on urban road and where the accident probability is greater than on rural roads or highways. To design suchintelligent systems, careful selection of sensors and detection algorithms is required.

3.1 ANALYSIS ON SENSORS:

Active sensors are very useful in providing real-time detection and show robustness under rainy and foggy conditions.Their main advantage is that some specific quantities (e.g., relative speed, distance etc.) can be measured without any powerfulcomputations. The long range detection (150 m approx.) of Radar based systems is more reliable in snow, foggy and rainyconditions than lidar.

However, a typical lidar is less expensive than radar but its range is relatively shorter. Modern high speed lidar systems (Velodyne HDL-64E) acquiring high resolution and 3D information of the scene are costly but have better accuracythan radar. Systems designed using these high speed scanners are able to acquire shape and classify the target vehicle intocar, bus, truck and motorcycle etc. Although providing useful information to

CAS, laser scanner technology has not yet beenintroduced to commercial market due to its high cost, the associated processing unit, and driver software. On the otherhand, radar and acoustic sensors collect less information about the target (e.g., shape, size, color etc.) and are more exposedto interference issues due to dynamic and noisy environment of road traffic. Noise removal and signal recovery may requirecomplex signal processing techniques. Prototype vehicles using active sensors have demonstrated promising results [21], [23], [25], but when numerous vehicles move on the same route, interference between sensors of the same kind creates issues. This type of sensors may also have other drawbacks, such as slow scanning speed and low spatial resolution.

The main advantage of optical sensors (cameras) is the low cost. With the development and advancement in technology, high performance and inexpensive cameras can be equipped on the rear and front side to cover full 360 degrees view. The visualdetection and tracking is independent of any modifications to the road infrastructure. Optical sensors can track more effectively the cars moving in a curve or during the lane change. They are also free from interference problems commonly faced by the active sensors. Another key advantage of using an optical sensor is its ability to provide a richer description about the vehicle's surroundings. Unfortunately, this type of sensors is not as robust as active sensor based techniques. Detection/classification is highly dependent on quality of captured images, which can easily be affected by the lighting, fog and other environmental conditions. Such systems require separate and more complicated image processing algorithms and higher computational resources to extract the required information from captured images.

Advances in stereo matching yield clean, less noisy and denser disparity maps for 3D vision. Improved stereomatching enables robust scene segmentation based on motion and structural cues [181]. Integration of machine learning algorithms can increase robustness of existent stereo vision approaches and simplify detection task. On the other hand, heavycomputations of disparity map require high speed hardware for their real-time implementation. Fusion of sensors may make thesystem more robust and reliable as multiple sensors can extract maximum possible information from the environment. Fusionof active and passive sensors has achieved better results in terms of classification and robustness.

4. CHALLENGES :

An important issue in the realization of a successful CAS is the design of vehicle detection systems with ultimate reliabilityand robustness in real-time. Considerable efforts have been made in this research area, several techniques and systems havealready been projected. Various prototype vehicles have been tested to demonstrate the effectiveness of proposed systems, a highly reliable, robust and real-time system is yet to be revealed. Google's self-driving car has been a big break throughtowards the development of autonomous vehicles equipped with modern sensors and CAS. This Google's fleet of roboticToyota Priuses has covered more than 190,000 miles of self-driving but this project is quiet far from becoming commercially viable because of cost and reliability issues.

Development of a real-world CAS suitable for urban roads is specially demanding because traffic jams,

motorbikes, bicycles,crossings, pedestrians, traffic signs and other participants pose additional challenges and diverse technical issues. The successof a CAS will depend on the number of correct detections versus the number of false alarms. We have categorized the overallchallenges into sensor challenges, algorithmic challenges and hardware challenges. We detail these challenges in followingsubsections.

4.1 SENSOR CHALLENGES:

Sensor selection is the first and most crucial step towards designing a reliable and robust CAS. Specific objectives include improving spectral sensitivity, dynamic range, spatial resolution, and incorporating computational capabilities. Active sensors perform well in different weather conditions and nighttime and their price is also in affordable range except 3Dlidar scanner such as velodyne HDL-64E (see Table I). Price of 75k USD is more than the price of car itself and therefore CASusing this scanner is undoubtedly too expensive.

Traditional cameras in the market lack the dynamic range required to operate in traffic under adverse lighting conditions.Day and night vision cameras are required to enable day time and nighttime operation without blooming. These cameras switch to Infrared (IR) mode when the light level falls below a threshold. SV-625B camera is an example for dayand nighttime application of an inexpensive optical sensor.

However, these sensors may have certain limitations such as narrow field of view. High resolution cameras with affordableprice offer significant advantages by capturing fine details of road environments. On the other hand, high resolution leadsto more data (pixels) to be processed causing an increase in processing time and requirement of powerful computationalresources.

Vision-based systems and algorithms are yet to evolve into more powerful techniques to deal with busy and complex trafficsituations. Fusion of multiple sensors could offer substantial improvements in CAS performance and it has the potential toyield a higher level of security and reliability. In multisensory approach, system is capable of acquiring more detailed and accurate environment features that are difficult to observe with a particular sensor. Extensive research efforts are required to design systems for effective data acquisition using multiple sensors.

4.2 ALGORITHM CHALLENGES

Development of vehicle detection algorithms which can work reliably and robustly in complex and changing environments (e.g., fog, nighttime, rain etc.) is for sure challenging.On-board cameras used for vehicle detection suffer from vibrational movement due to shocks, sudden brakes and engineoscillations. This affects the orientation and alignment of the captured video and involves recalibration of camera.

A practicalCAS should remain unaffected and performance invariant in the presence of such vibrational noise. Moving camera alsoprovides the video with constantly changing background and makes several well-established computer vision techniques(e.g., background subtraction) unsuitable to extract moving objects. CAS algorithms must be able to extract and identifyvehicles from rapidly changing and complex backgrounds with minimum false alarms.

In HG, appearance based clues have been very useful for estimating an initial ROI but most of them are for four-wheeledvehicles. In some countries (especially in ASEAN countries), a large number of motorcyclists appear on the road and theiraccident rate is higher than cars. There is a need of appearance clue(s)

which can accommodate motorcycles along with othervehicles on road. In HV, more focus is on feature and classifier based validation using different training datasets. A widerange of feature extraction algorithms have emerged but efforts should be continued to determine the best features which canextract the maximum information from objects (vehicles) and widely separate them from non-vehicle class. Such features willallow classifier to recognize a target vehicle better and reduce the number of false alarms by increasing the efficiency. Webelieve that more efforts are needed to develop powerful feature extraction and classification schemes.

Majority of vehicle detection systems reported in the paper have not been experimented under genuine conditions (e.g.,varying weather conditions, complex urban roads). Further-more, training and classifications are based on different datasets so comparison between these systems is difficult. This field is missing representative benchmarks for complete systemevaluations and fair comparisons. It is also worthwhile to mention that efficient and powerful algorithms addressing theabove mentioned challenges must be real-time since a small delay can make the whole CAS ineffective and unfeasible.

4.3 HARDWARE CHALLENGES :

On-board vehicle detection systems have high computational load as they must process the acquired data at real-time tosave time for driver reaction. The real time implementation is also linked with relative speed between ego vehicle andthe vehicle close to it. Greater the relative speed less is the time available for processing and driver reaction. Processingfrequency should be higher than 15 Hz (15 fps) to meet the real-time requirements. Most low-level image processing techniquesemployed in HG phase of vehicle detection carry out similar computations for all pixels in an image. Significant speed-ups can be attained by implementing these algorithms using GPUs which have parallel processors operating simultaneously.

Furthermore, pattern recognition algorithms are mostly computationally exhaustive and need powerful resources for real-timeperformance. With the drastic increase in computational power and speed of processors, we expect the availability of low costand more powerful CPUs and GPUs for CAS in the near future.

5. FUTURE RESEARCH

The majority of DAS and CAS reviewed in this paper have not been tested under realistic conditions (e.g., cluttered urban road environment, traffic jams, highways and different weather and illumination conditions). Future approaches should have their proposed systems assessed in real world and with online traffic data for feasibility study. Furthermore, the reported assessments to date have been difficult to compare since these arebased on different performance measures and data sets. Future research should build an online database as a benchmarking platform for comprehensive system evaluations and fair comparisons between different systems.

Future research should combine CAS with other DAS for the development of an autonomous car which can revolutionize transportation system in future. Google car is a good step forward towards designing a self-driving car but its test was conducted in a traffic-less environment and still huge effort is required to transform it into a practical autonomous car.

Improvements should be made in the development of fast and efficient DASs for high speed and

accident free autonomous driving. Rapid advancement in IC fabrication and availability of high speed multicore processors have enabled fast computation within a compact format. However, multiple DAS for self-driving car may require several sensors and processing units embedded as a single hardware unit. This may increase the cost for equipment resulting in expensive autonomous cars or cars with DAS. Studies should look for economical and small size hardware solutions which can make the product more affordable.

6. CONCLUSION :

In the past years, huge research efforts have been put in on-road vehicle detection techniques for CAS, especially automatic vehicle detection. It is obvious that key progress on CAS is made in terms of vehicle classification mainly due to fast computing resources, advance pattern recognition algorithms and efficient machine learning mechanisms. However, challenge still remains because of unreliable CAS and various on-road situations.

This paper critically and systematically analyzes the state of-the-art on on-road vehicle detection techniques for CAS. It starts with performance comparison of sensors, which infers that active sensors work well under different weather conditions, but face interference issues. State of the art 3D laser scanners (while expensive) can successfully classify target indifferent vehicle types. On the other hand, radar based systems lack this feature. Passive sensors gain more attention because of numerous advantages such as low cost, high resolution, easy installation, extracting brief information of surroundings and vehicle type classification. Cost and distance parameters are also considered while comparing different sensors, and cameras appear to be the optimal choice. This paper then introduces HG using motion and appearance based methods.

In HV, appearance-based approaches are more encouraging but recent developments in statistical and machine learning need tobe leveraged.In addition, motorcycle detection and tracking techniques are discussed since they require separate schemes due to their distinct size and shape. This part of review is important, especially in ASEAN region. At the moment, the existing technologylacks motorcycle detection and classification of identified targets into car, truck, motorcycle, pedestrian, bicycle etc. Thesepoints need special consideration and work out for future CAS design.

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