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 vehicle industries.**

***Index Terms*—Driver assistance system (DAS), motorcycle detection, sensors, tracking, vehicle detection.**

I. Introduction

EACH year approximately 1.24 million people around the world die on roads and between 20 and 50 million withstand 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% in middle income and 2% in high motorized countries [3]. This high fatality rate and economic costs have prompted the United Nation (UN) to launch a global program—"Decade of Action for Road Safety 2011–2020" in May 2011 [4].

Driver inattention, fatigue and immature behavior are the main factors causing road accidents. According to the National 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 the roadway)
- Cognitive distraction (e.g., being lost in thought)
- Auditory distraction (e.g., responding to a ringing cell phone)
- Biomechanical distraction (e.g., manually adjusting the radio volume)

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, increasing the possibility of an accident. Four common types of fatigue are:

- Local physical fatigue (e.g., in skeletal or ocular muscle)
- General physical fatigue (following heavy manual labor)
- Central nervous fatigue (sleepiness)
- Mental fatigue (not having the energy to do anything)

Immature driving behavior is also a main factor to cause road accidents, e.g., shortcut maneuvers that pose great threat to opposing vehicles, ignorance of traffic signals during late-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 because 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 reasons include:

- Lane splitting, i.e., driving between two lanes
- Ignoring traffic signs and road conditions
- Violating speed limits
- Driving on the wrong side of road
- Not using indicators at turns
- Driving while under the effect of drugs
- Vehicle (or motorcycle) faults
- Deliberate aggressive actions

Other than human errors, road and environmental conditions can also cause traffic accidents. The latter includes insufficiency

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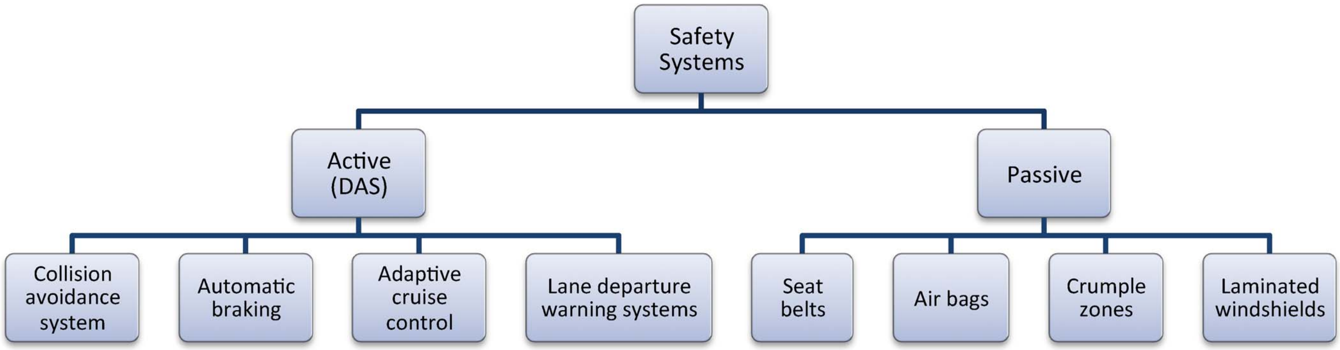

Fig. 1. Vehicle safety systems and their types.

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].

Since human behavior is the main cause for occurrence of accidents (where rear end collisions are the most common form [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. The latter such as seatbelts, airbags and crumple zones 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 collision avoidance systems, brake assistance and lane departure warning systems takes proactive steps to prevent an accident before it happens.

In this paper, we provide a review of sensors and techniques for vehicle detection and tracking for CAS, which is an automobile safety system designed to reduce the possibility of an accident. It is also recommend to read other comprehensive reviews [12] and [13] for driver safety systems. The first review [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, tracking and behavior analysis. This paper is different from [13] due to addition of survey on sensors (active and passive), their comparison and literature for motorcycle detection techniques. We focus on full system i.e., hardware and software solution for CAS while [13] addresses the driver behavior analysis and techniques for vehicle detection with minor details 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 or both).

In recent years, many commercially viable products related to CAS have been developed and equipped in the auto companies such as Volvo, Ford, Honda, Subaru, Mercedes-Benz, Toyota, and Nissan [14]. Some third parties, e.g., SmartEye and Seeing Machines, offer camera-based nonintrusive devices for CAS development such as Volvo cars [15], [16], where fusion of camera and radar is practiced [15]. The German company 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 (85 cm $\times$ 128 cm $\times$ 83 cm) and light weight (900 g); the LD-LRS2100 displayed in Fig. 2(b) has a range of 250 m, a coverage of 360°, and a 0.125° resolution [17].

(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].

The existing products have shown their effectiveness to the road safety, but they still suffer from issues in hardware such as sensor quality (optical sensors) and software including algorithm development [12], [18]. The former should meet the following factors: robustness (under various weather conditions), real-time data scan, and cost efficient solution. The latter should be fast and accurate enough to take initial action in CAS. There is tradeoff between the factors, i.e., more robust and accurate the products are, the higher price/cost may be. Unfortunately, for commercial products the cost is a critical issue to the vehicle consumers, i.e., if are they willing to pay more prices for the products? We focus on vision based systems for designing CAS 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 for vision based CAS. The aim is to find a combination of sensor and detection algorithm for an optimal CAS design. We argue that more focus should be placed on algorithmic side as progress in 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 numerous predictions for the development of CAS technology in the near future. This compels us to survey CAS techniques with their pros 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 for different scenarios (day, night, rain, fog etc.).

This paper is organized as follows: Section II introduces sensors (active and passive) for CAS. A survey on vehicle detection schemes is presented in Section III followed by various tracking algorithms in Section IV. Section V discusses existing detection and tracking algorithms followed by challenges in Section VI. Some directions for future research are proposed in Section VII and conclusive remarks are given in Section VIII.

II. Sensors For CAS

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

A. 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 and then track obstacles in front of vehicle. It was mounted in the front lower part (see Fig. 3) of an ego vehicle. The system calculated the distance between ego vehicle and target, and the relative speed by observing echoes of Radar signals. The system also worked well under various weather conditions and showed positive results (distance) for 150 m. A compressed sensing radar detection scheme based on sparsity of the cyclic autocorrelation was proposed in [25] for approaching vehicle detection, but only the simulation results were provided. Radar based driver safety systems were proved successfully in real time multiple lane vehicle detection by using discrete time signal processing [26]. Vehicles speed detection reached 90% of accuracy 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].

(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 speed of light, we can calculate how far the photons have traveled round trip. Typical 1D and 2D lidar sensors are inexpensive in production and easier in packing than radar. A laser scanner is an extended version of a laser range finder, which adopts the time-of-flight principle to calculate the distance to an object. The authors in [23] developed an approach to detect and 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 confidence level was computed accounting the geometrical configuration, the classification, and the tracking time. The system was then tested under several conditions (highways, urban centers) with three different Laser scanners for better accuracy. Modern laser scanners, such as SICK can collect high spatial resolution data with high scanning speeds and proved their usefulness for 200 miles test run conducted by United States Department of Defense Advanced Research Projects Agency (DARPA) [17]. Fig. 4 shows a modern 2D laser scanner mounted on the front end of a vehicle.

More recently, Velodyne has designed small size 3D lidar sensor HDL-64E for obstacle detection and navigation of

(a) (b)

Fig. 5. (a) 3D Lidar sensor HDL-64E; (b) The same scanner mounted on the top of Toyota Priuse.

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-selectable frame 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.

B. 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 vehicle based on acoustic cue has been proposed [30]. First, it extracted a robust spatial feature from noisy acoustical observations by employing gradient method. Then, the spatial feature is filtered out through sequential state estimation using particle filter. The proposed system was tested with real world acoustic data, which was obtained by the vehicle-mounted microphones outside the cruising vehicle. Authors in [29] presented a comprehensive design of an acoustic sensing hardware prototype to detect vehicles by estimating congestion on the road using the negative feature (noise) of urban road environment. It sampled and processed road noise to calculate several metrics such as vehicle speed distribution and vehicular honks, with speeds estimated from honks using differential Doppler shift. The metrics were then transferred to a remote server over General packet radio service (GPRS) every minute. Based on these metric values, server (a remote processor) determined the traffic condition on the road. Moreover, motorcycles were detected using three unidirectional microphones in a microphone array through its unique low frequency signal components [28]. Their locations on the sensor platform were carefully selected through a series of experiments and analytical analysis. Algorithms were developed to compensate the acoustic signals saturation because the signals had more low-frequency components and could cause false detection.

Optical sensors/vision-based CAS are utilized to track approaching and preceding vehicles more effectively than active sensors as visual information can provide a brief description of the surrounding vehicles [31]–[33]. Detection may be carried out by using stereo camera [41], single [35], [36] or multiple cameras [37], [38]. The cameras can be mounted either on the inner side of wind screen near the back view mirror or on the rear side of body of vehicles. In many cases, multiple cameras may 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 detection and 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 set of AdaBoost detectors were trained for multiple vehicle views and candidate regions were verified by looking for peaks in the disparity range. Monocular vision had the advantage of detecting two objects which lie close to each other in 3D space and cause a typical miss in case of stereo-vision approach [44]. Monocular vision and stereo vision were also utilized to work in cascade where the former was used to generate vehicle candidate regions, and the latter to verify those regions as vehicles, by searching for vertical objects in the 3-D domain [45]. Table I summarizes the existing active and passive sensors in terms of strengths and weaknesses.

C. 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 one sensor detects while the other validates [48], [49].

1) Radar and Vision: Radar-vision fusion for on-road vehicle detection and perception has received more attention in recent 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 symmetry feature of the limited region in images (ROI) detected vehicles [51]. In similar approaches [59], [60], vehicles were detected using symmetry, edge information and optical flow features of images. Kalman filtering on radar data was employed for tracking and ranging of identified vehicles. Classifier based detection using HOG, Haar and Gabor features, and range finding by radar was successful in [57], [61]. In another study [58], the input image was analyzed for salient locations using a variety of visual features including orientation, intensity, color, and motion. Once the vehicle became known, its distance was calculated from radar and vision fused data. Monocular vision was used to solve structure from motion, with radar providing probabilities for objects and the ground surface [62].

TABLE I
SUMMARY ON 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

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 occupancy grid; vehicles were tracked with Kalman filtering in a global frame of reference [52]. In [63], a radar-vision online learning framework was utilized for vehicle detection.

2) 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 lidar was 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 approach using Radar, vision and lidar technologies with widely overlapping fields of view. Two independent Laser scanners and several overlapping short range Radar sensors were mounted on the sides of car, and front was covered by three powerful long-range sensors (i.e., stereo-vision, radar, and laser). By considering confidence and reliability measures for all sensors, the obstacle map estimated by sensor fusion was revealed to be more reliable and precise than any of individual sensor outputs.

3) Acoustic and Vision: Chellappa *et al.* [67] took advantage of complementary information obtained by fusing acoustic and video 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.

4) Radar and Lidar: System based on collective information acquired by Radar and lidar developed in [68] produced salient obstacle 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 detection and tracking.

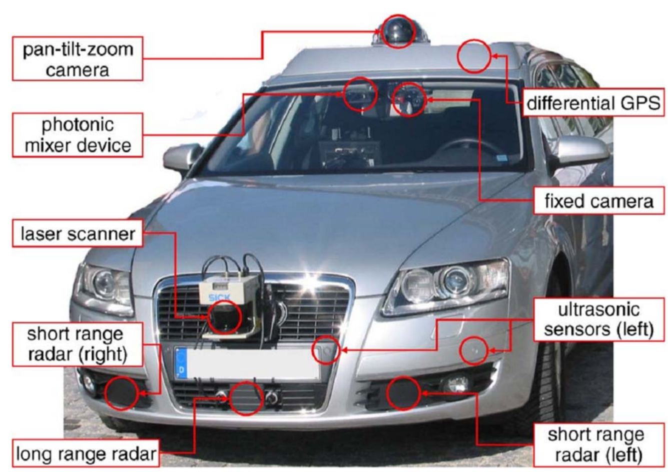

Fig. 6. Test vehicle used to acquire road traffic scenes for evaluation.

5) Other Multiple Modalities: Recently, the authors in [28] applied fusion of Radar, sound sensor, stereo and IR camera to detect and monitor the motorcycle motion. The system was mounted on one nearby pole and more robustness and reliability were achieved. A safety system was presented in [69] where a test vehicle (Fig. 6 provided by Audi was equipped with two high-resolution video cameras, one time-of-flight laser

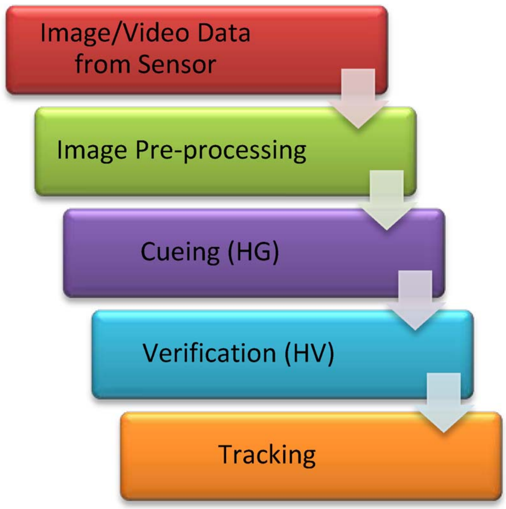

Fig. 7. Stages in vision-based vehicle detection and tracking system.

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.

III. Vehicle Detection Schemes

Imaging technology has immensely progressed in recent years and cameras are cheaper, smaller, and of higher quality than ever before. Moreover, computing power has dramatically increased and we have witnessed the emergence of computing platforms geared toward parallelization, such as graphical processing units (GPUs) and multicore processors. These hardware developments allow real-time implementation of computer vision approaches for vehicle detection.

The vehicle detection system can be structured as seen in Fig. 7, where image preprocessing removes noise and may involve contrast adjustment while Cueing/Hypothesis Generation (HG) and Hypothesis Verification (HV) stages play key parts. HG aims to spot the potential vehicle locations in the captured image and identify them as regions-of-interest (ROI); HV validates the identified candidates as either vehicle or non-vehicle. Once it is verified, its movement in next video frames is then monitored using a tracking function. The quantity of information to be processed is reduced when the detection process moves from one stage to the next. This allows more sophisticated processes to operate on a smaller portion of the image.

Following subsections review existing techniques on cueing and verification stages mainly based on vision-based vehicle detection techniques.

A. Cueing Stage

Usually in systems with radar and vision fusion, ROIs are determined by analyzing the distance and the relative speed information accumulated by radar. Systems with stereo cameras

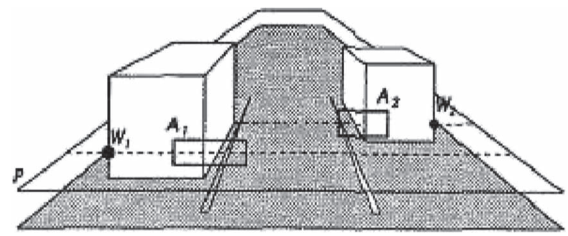

Fig. 8. Search windows (A1 and A2) are set up on plane P to group the corresponding clusters for each vehicle [80].

use disparity map or inverse perspective mapping to locate regions for vehicle presence [70]–[72]. Vehicle's motion or appearance features are exploited to determine ROIs in images obtained from optical sensors. The motion based techniques require the analysis of several image frames to detect moving objects based on their optical flows. However, appearance based vehicle detection analyses a single image to find visual cues to hypothesize vehicles' locations. Whereas, stereo based cueing approaches may either be motion based or appearance based. Following subsections explain these techniques and review the representative literature.

1) Motion Based Approach: Motion based techniques exploit the temporal information in sensor data to detect vehicles. Optical flow fields from a moving vehicle are calculated by matching feature points or pixels between two image frames. Dense optical flow proposed by Horn and Schunck [73] matched the intensity of all pixels in image. Sparse optical flow tracked a set of particular features such as corners [74] or color blobs [75] of a vehicle. After calculating the optical flow fields, moving vehicles including were segmented from the image by clustering the fields based on their positions, magnitudes and angles.

A motion based vehicle detection system called "*Scene Segmenter Establishing Tracking* (ASSET-2)" was proposed by Smith in [74]. The system employed features based (sparse) optical flow for motion estimation. First, the corner features in the image were extracted using either the *Smallest Univalue Segment Assimilating Nucleus* (SUSAN) [76] or Harris [77] corner detectors. Then, features were tracked over several frames to create the optical flow fields. A 'flow segmenter' was used to cluster the fields based on their flow's variations. Finally a bounding box and centroid of resulting clusters were calculated and hypothesized as vehicles. The system required high computational load and therefore they used special hardware acceleration to attain real-time performance.

A similar vehicle detection system proposed in [78] utilized SUSAN features to estimate the sparse optical flow fields and improved the flows calculation using 3-D Pulse Coupled Neural Network (PCNN) [79]. They showed that detection accuracy depends on the relative speed between the host and preceding vehicles. Vehicles with small relative speed (<10 km/h) achieved low detection rate (69.1%). A technique for grouping clusters of optical flow into individual moving objects was suggested in [80] (Fig. 8). Firstly, the detected clusters were projected into a plane (P) parallel to the road surface. By starting at an outer boundary point W, a search area was set

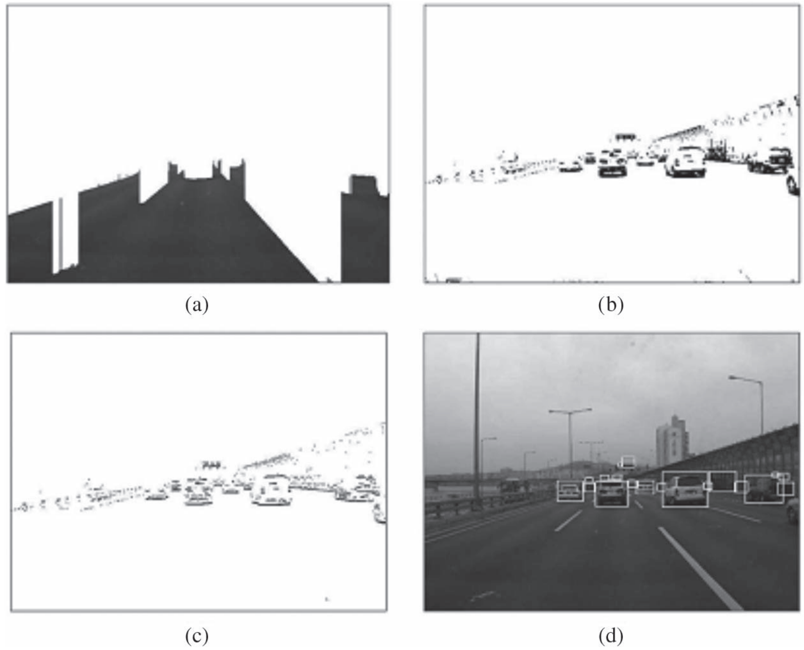

Fig. 9. (a) Road region, (b) shadow region, (c) horizontal edges in shadow region, and (d) HG by the shadow region [82].

up based on the expected minimum and maximum widths of the vehicle. If the search was successful, a coordinate was calculated using the coordinates of all matched flow clusters located in that region. This coordinate was later required to estimate width and center point of the vehicle.

Based on optical flow technique, a DAS was implemented on INTEL XScale PXA270 SoC-based embedded hardware platform with a few peripheral devices [81]. A CMOS camera was connected to the hardware platform with a USB interface and attached to the inner side of windscreen of a test car to acquire a QVGA (320 by 240) resolution image at 30 frames per second (fps). The system was tested on highway and experimental results showed an average detection time of 0.16 s per vehicle and 95.8% correct detection rate.

2) Appearance Based Approach: Appearance based cueing techniques use specific appearances of a vehicle's view for ROIs extraction such as. shadow under vehicle [35], [36], [82], edges [83], corners [34], symmetry [84]–[89], texture [90], color [91] and lights of vehicle [92], [93].

a) Shadow Feature: Shadow under vehicle provides a cue for vehicle existence since it is darker than the adjoining road surface. This can be observed in various ways, for example, in [35], histogram of paved road was evaluated to find a threshold for segmenting shaded areas. Regions of shaded areas in the images together with edge information were used to hypothesize the location of vehicles. A more intelligent approach using shadow for proceeding vehicles was designed as seen in Fig. 9 [82]. Initially, road regions (driving space) were extracted by outlining the lowest central homogeneous region in the image delineated by edges (9a). Then, areas with intensities smaller than a threshold value were declared as shadow regions (9b). After that, horizontal edges of these regions were extracted and based on locations of these edges (9c); hypotheses were determined (9d).

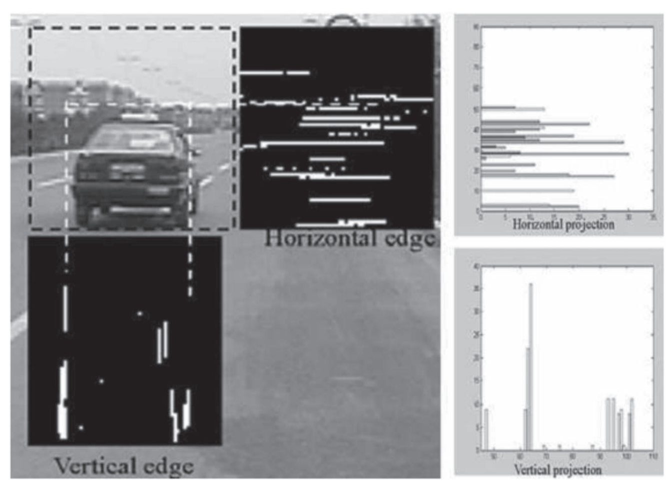

Fig. 10. Edge based vehicle cueing [92].

b) Edges Clue: Most vehicles' rear view show horizontal and vertical edges and this may be useful for ROI generation. A group of horizontal and vertical edges that form a rectangular shape with an aspect ratio between 0.4 and 1.6 are good candidates for potential vehicles [94]. The clue had been employed to locate position of a vehicle after initial ROI was found based the cue using the shadow underneath the vehicle as illustrated in Fig. 10 [95]. Zehang *et al.* [96] proposed a multi-scale approach to detect a vehicle's edges using three different image resolutions. Betke [83] suggested a coarse to fine search technique in which the coarse search identified groups of prominent edges and finer search performed on these regions detected rectangular shaped objects. The approaches above may not be able to detect motorcycles and bicycles. Therefore, in [97], [98], along with edges, shadow and black

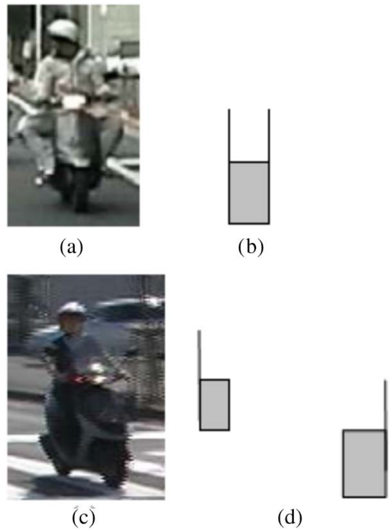

Fig. 11. Edge and color clues for ROIs [95].

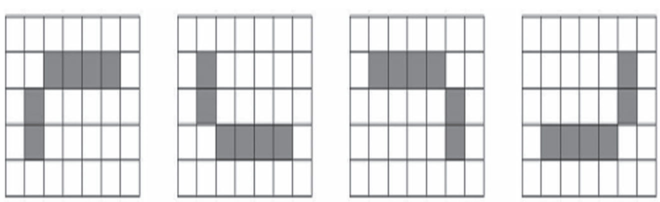

Fig. 12. Four different masks used to detect four corners of a rectangle [34].

color of tire were also exploited to determine the possible locations of motorcycles (Fig. 11).

c) Symmetry Property: Most vehicles' front or rear views are symmetrical over a vertical center line. Therefore, it is possible to estimate the locations of vehicles in the image by detecting the regions with high horizontal symmetry [84]–[89]. Generally, the symmetry detection techniques require a symmetry operator to calculate the symmetry value of an image region. The value is obtained based on different pixel characteristics including gray values, binary contour, gradients, color and feature points. Zielke *et al.* [89] suggested a scheme to identify the centerline of leading vehicles using the image intensity symmetry. The bounding box for a vehicle was drawn by performing edge detection and locating pairs of edges which were mutually symmetric with respect to a detected symmetry axis. Kuehnle *et al.* [87] recommended three different symmetry criteria for locating vehicles: gray level symmetry, contour symmetry and horizontal line symmetry. The histograms generated from these criteria were used to find the vehicle's centerline.

d) Corners: The general shape of a vehicle is rectangular with four corners. This was performed to identify all possible vehicle's corners in the image using the template in Fig. 12 [34]. A possible vehicle was detected if there were four matching corners with enough edge pixels at the positions corresponding to vehicle's sides. The corner detection process could be speeded up by using a common double-circle mask to detect all types of corners [99]. Detected corners were then clustered based on their types and locations. Finally, the features of corners in each

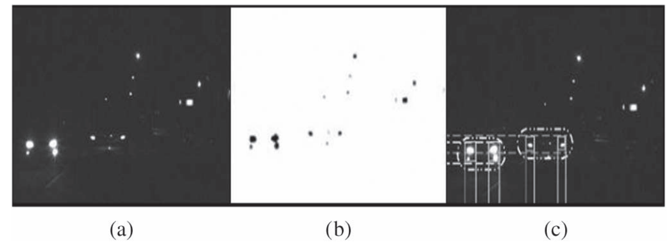

Fig. 13. Vehicle detection based on tail lights: (a) Night time road environment. (b) Bright objects extraction. (c) Result of spatial clustering of bright components [93].

cluster were extracted and used as an input to Support Vector Machine (SVM) classifier to determine whether it belonged to the vehicle.

e) Color: Most vehicles have a homogeneous color (body color and signal light color) that is different from road surface and background objects. This had been exploited to segment vehicles from the images by using a color transform model to define the important 'vehicle color' [91]. On the other hand, the pair of red brake lights and yellow signaling lights such as the tail lights was regarded as a cue for vehicle detection with color segmentation techniques [100].

f) Texture: The texture of vehicles varies from their surroundings such as road surface, buildings and vegetation. Statistical analysis on entropy [101] and co-occurrence matrix [102] were performed to segment out ROIs in images.

g) Multiple Cues: It is possible to combine multiple cues for vehicle detection [36], [83], [103], [104], for instance, Leeuwen *et al.* [36], merged shadow, entropy and symmetry features. It started with the establishment of all image regions that potentially belong to the shadow. Then, all rows with low entropy in the detected region were removed and their horizontal intensity symmetry was checked to determine whether or not it belonged to a vehicle. Moreover, shadow, symmetry, vertical edge, and taillight were combined in [105] to identify vehicles under various lightning conditions and tracked with particle filter (PF) framework. This fusion resulted in 92% of detection and precision rates.

h) Headlights/Taillights (For Nighttime Detection): Performance of ordinary vision sensor is seriously affected in poorly illuminated or nighttime conditions. Light reflection caused by the motion of vehicles distorts the information in image/video data. Therefore, most of the techniques discussed in this paper are not reliable for performing nighttime vehicle detection. Nighttime environments are challenging because the appearance clues (e.g. shadow, edges, tire color) fail to deliver. Vehicle head and tail lights are the only characteristics which can be utilized for hypothesizing and detecting vehicles during nighttime. Several techniques [40], [93], [106]–[112] have been developed by researchers to detect vehicles using either headlights or taillights or both, and are discussed below.

Chen *et al.* [93] segmented bright objects in the image and after their spatial clustering, verified the target regions with symmetric properties, i.e., shape, texture, and relative position (see Fig. 13). Candidate regions were extracted using color clue and selected candidate pixels for signal lights by statistical features. Remaining regions were inspected for circular shapes because most light sources are round in shape [106]. A novel image-processing technique segmented tail lights of preceding vehicle from forward-facing color video using a red-color threshold in hue, saturation and value (HSV) color space. Lamps were then paired using color cross-correlation symmetry analysis and tracked using Kalman filter [107].

Red color detection of tail lights localized ROIs and their distance was calculated to develop a predictive brake warning system. 50 samples were collected for brake light distribution data which was later used to find the threshold [108]. Authors in [111] suggested a methodology that utilized a perspective blob filter to explore light pairs, separated headlights from tail-lights and distinguished between cars going same or opposite way. Gaussian filter and clustering approach detected pairs of circular lights under various lightening conditions. The brake light activity of preceding vehicle was observed to estimate its maneuvers. The system was able to differentiate headlights from taillights using color based comparison. Vision and sonar sensors had identified and tracked vehicles under various road and light conditions. Several images were compared to decide light condition before processing and select either day or night-time detection algorithms to activate.

Nighttime algorithm extracted and verified bright regions corresponding to front, back and brake lights [107], [109]. Vehicles were recognized by using features extracted from four steps: 1) taillight recognition process; 2) adaptive thresholding; 3) centroid identification; and 4) taillight pairing algorithm [110]. Medium and low mounted video cameras (4 to 15 m. high) had been successful in detecting headlight pairs during nighttime. Furthermore, appearance features of other vehicles were retrieved by detecting pair of headlights and tracking module was added to increase robustness against partial and complete occlusions [112]. Jisu *et al.* [40] proposed a vision-based vehicle detection system with normal and infrared (IR) camera sensors, and using an efficient feature extraction algorithm. In cueing phase, neighborhood gradient prediction (NGP) scheme was applied for effective edge detection and SVM trained on HOG and GABOR features was used for classification in verification phase.

3) Stereo Based Approach: In this approach, multi-view geometry allows direct measurement of 3-D information, which provides understanding of scene, motion characteristics, and physical measurements. The variation in left and right images between corresponding pixels is called disparity and stereo matching of disparities of all image points calculates the disparity map [113]. If the parameters of stereo rig are known, the disparity map can be transformed into a 3D view of the observed scene [114]. The v-disparity has been widely used to model the ground surface, in order to identify objects that lie above the ground [115]. The v-disparity forms a histogram of disparity values for pixel locations with the same v, i.e., vertical image coordinate. The v-disparity can extensively be used in stereo vision for intelligent vehicles [42], [115]–[121].

Techniques have been proposed which used monocular appearance features for vehicle detection using a stereo rig including color [122] and image intensity [41]. Authors combined features such as size, width, height, and image intensity in a Bayesian model to detect vehicles using a stereo rig [41]. Potential vehicles were identified and segmented by calculating histogram of depths from stereo matching [43]. Clustering was implemented using a modified version of iterative closest point, using polar coordinates to segment objects. It was able to detect vehicles and infer the vehicle's pose with respect to the ego vehicle [123]. A two-stage mean-shift algorithm detected and tracked the traffic participants with a long-term motion prediction (1–2 s into the future) in a dynamic scenario. The first stage employed a gray value histogram as a target model and the second stage was a refinement of the object pose largely along the depth axis [124]. The concept of 6D vision, i.e., tracking of interest points in 3D using Kalman filtering, along with ego-motion compensation identified moving and static objects in the scene [125].

Optical flow had been considered as a fundamental component of stereo-vision analysis of the on-road scene in [43], [117], [124]–[131]. Block-based coarse-to-fine optical flow was compared with the classical Lucas-Kanade optical flow [30] and was found more robust to drifting [130]. The object flow descriptor [132] was used to understand whether the ego vehicle is at an intersection or arterial road by modeling the aggregate scene flow over time. Scene flow modeled the background motion, and regions whose motion differed from the scene flow, were categorized as candidate vehicles [128]. Table II summarizes the vehicle cueing techniques and their limitations.

B. Verification Stage

Verification techniques can be categorized into two groups: (1) correlation based approaches using template matching and (2) learning based approaches using an object classifier.

1) Template Matching: The correlation based method uses a predefined template and determines a similarity measure by calculating correlation between the ROI and the template. Since there are various models of vehicles with different appearances, therefore, a 'loose' and general template with common features of a vehicle is used. These features include the rear window and number plate [133], a rectangular box with specific aspect ratio [134] and a "U" shaped pattern with one horizontal and two vertical edges [135]. A vehicle could appear in different sizes depending on its distance from the camera; therefore, the correlation test is usually performed at several scales of ROI. Intensity of the image is also normalized before the correlation test to get a consistent result.

Dynamic templates had been proposed in which once a vehicle is detected with a generic template, the template for subsequent detection is created online by cropping image of the detected vehicle [136]. Template update increased the robustness of template matching technique and its reliability was measured using edges, area and aspect ratio of the target. The online update was only performed when this reliability measure exceeded a certain threshold [137]. Authors in [138] applied dynamic template method and quality of matching was monitored by estimating 'vitality' values. The 'vitality' of a tracked vehicle increased when there was a sequence of successful template matching, while it decreased after a sequence of bad matches. When the 'vitality' value fell to zero, the vehicle was

TABLE II
HYPOTHESIS GENERATION SCHEMES AND THEIR LIMITATIONS

Type	Technique(s)	Methodology and/or Advantages	Limitations
Motion based	**Optical Flow** [78, 81]	• Calculated by matching pixels or feature points between two frames. • 60% to 90% detection rate for 5km/h to 25km/h relative speeds respectively	• High Computational Load • Low detection rate (60%) at small relative speed (5km/h) • Camera movement sensitive • Fails to detect slow moving objects • Requires analysis of several frames before detection
Appearance Based	**Shadow underneath vehicle** [35, 82]	• Image thresholding approach • Easy detection by morphological operations • Less computations	• Fails when colour of the road pavement is uneven • Affected by shadows from nearby buildings, overhead bridges or trees. • In morning and evening, long shadows generate incorrect ROIs • Motorcycle shadows are always on side
	Corners [34, 99]	• Find corners with enough edge pixels. • Clustering based on corner types and locations.	• Fail in Cluttered and complex Environment
	Vertical and Horizontal edges [95-98]	• Fixed ratio of horizontal to vertical edges for regions with targets (vehicles) • Easy Computation	• Interference from outlier edges • Difficult to select an optimum threshold
	Symmetry [84-89]	• Vehicles' rear or front views are vertically symmetrical • Hypothesize ROIs by detecting vertical symmetry. • Better ROI estimation	• Higher computational load • Needs a rough estimate of target location in image
	Colour [91, 100]	• Simple histogram calculations • Useful in night time detection	• Performs poorly with background of matching colours. • Illumination dependent
	Vehicle's lights [93, 139]	• Only cue for night time detection • Bright objects extraction and segmentation. • Heuristic rule-based techniques for analysing the light patterns.	• Mix up with street lights or bulbs outside shops • Headlight fault in vehicles can produce false alarms for motorcycles
	Stereo cameras [41, 42, 115-125, 140, 141]	• Computes disparity map to get 3D map. • A peak in histogram bin will indicate an obstacle within the depth of interest. • Transformation and re-projection methods catch moving objects. • Small size detection	• More expensive than ordinary cameras • Calculation of disparity map is computational hungry • Require high speed hardware for real-time operation
	Multiple features [36, 83, 103, 104]	• High precision rate due to better localization • Increased system robustness • More reliable	• Computationally Expensive • Time consuming

assumed to be no longer valid and it was removed from the tracking list.

2) Classifier-Based Vehicle Verification: This approach uses two-class image classifiers to differentiate vehicle from non-vehicle candidates. A classifier learns characteristics of a vehicle's appearance from training images. This training is based on a supervised learning approach where a large set of labeled positive (vehicle) and negative (non-vehicle) images are used. The most common classification schemes for vehicle verification include Artificial Neural Networks (ANN) [142], SVM [143], AdaBoost [144] and Mahalanobis distance [145]. To facilitate the classification, training images are first preprocessed to extract descriptive features. Selection of features is important for achieving good classification results. A fine set of features should capture most of the variability in the appearance of a vehicle [146]. Numerous features for vehicle classification have been proposed in literature including Histogram of Oriented Gradient (HOG) [147], [148], Gabor [149], Principal Component Analysis (PCA) [150], [151] and Haar wavelets [152], [153].

HOG feature captures local histogram of an image's gradient orientations in a dense grid and it was first proposed by Dalal [147] for human classification. System developed using a linear SVM classifier trained on HOG features was able to spot vehicles in different traffic scenarios but no quantitative result was given [154]. Paul *et al.* [148] achieved 88% accuracy in classifying the orientation of a vehicle with SVM classifiers trained on a set of orientation specific HOG features. Three oriented Haar wavelet responses: horizontal, vertical and diagonal computed at different scales were subjected to SVM training and produced 90% detection rate but with high number of false detections (10 per image) [152]. The richer set of Haar-like features had detected cars and buses from video images but only 71% detection rate (at 3% false detection) was achieved [153].

TABLE III
HV SCHEMES

Type	Technique	Methodology	Quantitative Results	Resources	Task/Goal(s)		
					Detection	Tracking	Classification
Correlation Based	Template Matching	• ROI based on symmetry map • Model matching of corners and aspect ratio of rectangular box [134]	59ms (~17fps) detection time	Intel Core i7 with 3.4GHz Linux OS	✓	✓	×
		• Image entropy and shadow analysis for ROI • The partial Hausdorff distance for HG • Classification by Hausdorff distance [135]	Execution time per frame 33ms or (30fps)	Intel Core i7 with 3.4GHz Windows 7 MATLAB 2014a	✓	✓	✓
		• Combination of color, edge, and motion information for ROI • Online template matching and temporal differencing approaches for recognition [136]	Processing time per frame is 17ms (60 fps)	Intel Core i7 with 3.4GHz Windows 7 MATLAB 2014a	✓	✓	×
		• Vertical edge and shadow features for ROI localization • Dynamic template matching for tracking [137]	Performance rate of 95.7% Average processing time of 170ms (~6fps)	Intel Core i7 with 3.4GHz Windows 7 MATLAB 2014a	✓	✓	×
		• Camera motion analysis for motion detection and tracking by clustering segmentation • Template update by horizontal edge detection and shape recognition [138]	16fps performance rate	Intel Core i7 with 3.4GHz Windows 7 MATLAB 2014a	✓	✓	×
Learning Based	Features and Classifiers	• Histogram of Oriented Gradient (HOG) with SVM classifier [148]	88% classification accuracy	Intel Core i7 with 3.4GHz	✓	×	×
		• HOG feature with linear SVM classifier [154]	---	Sony XR520 camera MIT car dataset INRIA data set	✓	✓	×
		• Haar wavelets transform with SVM classifier [152]	90% detection rate 28fps performance rate 5.3ms per obstacle detection	Intel Core i7 with 3.4GHz	✓	×	×
		• Haar like features with AdaBoost algorithm [153]	71% detection rate 38fps performance rate	Intel Core i7 with 3.4GHz	✓	×	×
		• Gabor features trained on the SVM classifier [149]	94.8% detection rate 30fps performance rate	Intel Core i7 with 3.4GHz	✓	×	×
		• Boosted Gabor features and an SVM classifier [160]	96% detection 28fps performance rate	Intel Core i7 with 3.4GHz	✓	×	×
		• Combination of Gabor and Lagendre moment features with SVM [161]	Detection rate of 99.1% up to 70m distance	Monochrome CCD camera 1.8 GHz PC	✓	×	✓
		• With neural network	Detection rate of 95.8% up to 70m distance				
		• Principal Component Analysis (PCA) with SVM [151]	Reported 95% detection rate	MIT vehicle datasets INRIA objects dataset Visual C++ with OpenCV	✓	×	×
		• Comparison of different features and classifiers [18]	**PCA:** SVMs yielded an error rate of about 8% lower than NNs **SVM:** The smallest error rate for • PCA features was 9.09%, • wavelet features was 6.06% • Gabor features 5.33% • Wavelet + Gabor Combined feature set 3.89%	Pentium III 1133 MHz Sony x-view CCD camera	✓	×	✓

Gabor features had been known for texture analysis of images [155]–[158] as they capture local lines and edges information at different orientations and scales. SVM classifier trained on Gabor features were tested for vehicle detection and achieved 94.5% detection rate at 1.5% false detection [149]. It was showed that the classifier outperformed a PCA feature based ANN classifier. A systematic and general evolutionary Gabor filter optimization (EGFO) approach to select optimal Gabor parameters (orientation and scale) was investigated to improve vehicle detection [159]. SVM classifier trained on Boosted Gabor features with parameters (orientation and scale) selected from learning had reported 96% detection rate [160]. Combination of Gabor and Lagendre moment features outperformed the Haar wavelets features for vehicle detection. The combined performance of features was evaluated on SVM classifiers and reported a detection rate of 99% at 1.9% false detection [161].

PCA reduces dimension of the image data by projecting it into a new sub-space (Eigen space) and extracts the representative features. Truong *et al.* [151] performed PCA to build a feature vector for vehicle, naming it 'Eigen space of vehicle'. An SVM classifier was adopted for classification which resulted in 95% detection rate. Authors in [162] concatenated symmetry measure, shadow model likelihood measure and rectangular likelihood measure to form a feature vector for classification. The Mahalanobis distance between a candidate's feature vector and the vehicle's class centroid decided whether it belonged to a vehicle. 92.6% detection rate and 3.7% false detection was reported by this technique.

A texture based vehicle classification technique calculated features using the Co-occurrence Matrix [163] and utilized a Multilayer Perceptron (MLP) ANN for classifying candidate images into car, truck or background. However, no quantitative result was given [164]. A technique similar to HOG for feature extraction but instead of calculating the histogram of gradient, histogram of the redness measure for taillights was calculated. The AdaBoost learning algorithm recognized the rear view of Honda Accord cars and reported 98.7% detection rate at 0.4% false detection [165]. Table III summarizes the vehicle verification techniques, lists their performances and resources used.

In addition, the classifiers have been used especially for motorcycle detection. The authors in [166] applied SVM for motorcycle detection regarding helmet as a key feature. The SVM was required to train on histograms of head regions of motorcyclists. Heads of the riders were extracted and classified into helmet and non-helmet groups by SVM. The classifier was integrated with a tracking system (seen in session IV) where motorcyclists were automatically segmented from video data. Techniques proposed in [97], [98] showed successful classification and tracking of motorcycles on urban roads. Prior

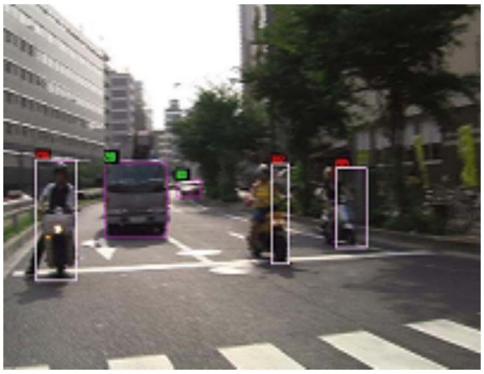

Fig. 14. Motorcycle detection by SVM Classifier [97].

information was used to find out the possible candidates for potential motorcycles. The system had large database of positive and negative images for SVM training, and then SVM classified the candidate regions into motorcycle and non-motorcycle objects. Once the motorcycle was identified, tracking was then performed (seen in session IV). The proposed system was also capable of detecting multiple motorcycles in a single frame as shown in Fig. 14.

IV. TRACKING

Tracking takes advantage of temporal continuity in data and significantly improves accuracy and time for vehicle detection. It serves two major purposes: estimation of motion and position of vehicles; maintaining awareness of previously detected vehicles that were not detected in a given frame [167], while filtering out spurious false positives [168]. On the other hand, tracking may face issues like measurement and sensor uncertainty, data association and track management. When tracking output declines, common hypothesis generation techniques set up to maintain performance levels. In most cases, monocular tracking methods measure dynamics in terms of pixels, whereas stereo-vision methods estimate dynamics in meters.

Conventional tracking and Bayesian filtering techniques have been widely used in monocular vehicle tracking [105], [131], [169], [170]. The state vector often consists of the vehicle's lateral and longitudinal position, width and height, as well as velocity. The state of a system $\mathrm{x_k}$ [seen in (1)] is governed by (linear/nonlinear) stochastic difference equations with the measurement $\mathrm{z_k}$ [seen in (2)].

$$\mathrm{x_k} = \mathrm{A}\mathrm{x_{k-1}} + \mathrm{B}\mathrm{u_k} + \mathrm{w_{k-1}} \tag{1}$$

$$\mathrm{z_k} = \mathrm{H}\mathrm{x_k} + \mathrm{v_k} \tag{2}$$

The random variables $\mathrm{w_k}$ and $\mathrm{v_k}$ represent the process and measurement noise (respectively). The matrix A relates the previous state to the current state and matrix B relates the optional control input u to the state x whereas, H in the measurement equation relates the state to the measurement.

Kalman [171] or Particle filters (PF) [172] with different sensors are frequently employed for track and to estimate the motion of detected vehicles in image planes. In the following subsections, we review some vehicle tracking approaches involving Kalman filter, Extended Kalman filter and Particle filters.

1) Tracking With Kalman Filter: The Kalman filter was firstly proposed in 1960 and since then it has been used successfully in several estimation and tracking applications [173]–[175]. It estimates the optimum state of a linear time-invariant motion model assuming process and measurement noises to be Gaussian. The prediction step extrapolates the position of target objects in next frames using a constant velocity constraint. The correction step regards detection as measurement and updates the filter state.

Kalman filter predicted locations of vehicle candidates in the image plane in which measurements were determined by a local search over the image patch for similar feature scores [167]. This approach was able to take measurement even if the detector failed in a particular frame. A set of constraints and assumptions was used to estimate 3D coordinates from monocular vision and Kalman filtering was applied to track vehicles [176]. In similar studies [177]–[179], 3D information was extracted from ground plane estimation and visual data to detect the moving vehicles while Kalman filter performed the tracking function.

Kalman filtering has been widely used in stereo-vision for vehicle tracking and disparity filtering [129]. Noise in stereo matching is generally modeled as white Gaussian [125] and filtering over time can produce cleaner disparity maps [180]. Kalman filtering was used to track individual 3-D points [125] and stixels, i.e., intermediate vertical elements of near-constant depth, which were fit to cuboid vehicle models [181]. Authors detected vehicles in the monocular plane using an AdaBoost-based classification and tracked in 3D using Kalman filtering [43], [182]. Kalman filter tracked objects detected by clustering approach [170], while it estimated vehicles' yaw rate, as well as position and velocity in [131], [169].

2) Tracking With Extended Kalman Filter: In reality, vehicle motion is nonlinear, with the vehicle's yaw rate describing the vehicle's turning behavior. This introduces non-linearly in difference or measurement equations or both. Kalman filter is no longer applicable in these cases so therefore, the Extended Kalman Filter (EKF) is recommended for estimation and tacking purposes. The EKF had been applied to estimate the yaw rate and the corresponding turning behavior of vehicles in [183], [184]. A side-mounted stereo rig observed nonlinear motion of vehicles with respect to the camera's frame of reference [185]. This nonlinear motion was successfully estimated and tracked with an EKF. Authors had applied EKF for the ego motion estimation with independently moving objects' position and motion estimated by Kalman filtering [127].

3) Tracking With Particle Filter: PF is a numerical method that determines an approximate solution to the sequential estimation and has been successfully applied in single and multiple objects tracking problems [172]. It is effective for solving non-linear, non-Gaussian, problems with Bayesian approximation implementation using Monte Carlo simulations [186]. In PFs, the required posterior density function is represented by a set of random samples (particles) with associated weights. Finally, the state is estimated on the basis of magnitudes of weights associated with each sample.

The PF was also introduced into the computer vision domain [187] as an alternative to the EKF's estimation of nonlinear parameters in traffic videos in [188]–[191]. For example, the authors in [192] tracked vehicles and estimated their 3D position and yaw rate using a PF. It mapped the motion to full trajectories learnt from prior observational data. The PF could also be used as occupancy cells and as tracking states for detected objects and obstacles [126].

V. Discussion

On-road vehicle detection has always been the major focus in vehicle industries. The introduction to CAS in modern cars may reduce the accidents rate by quickly and robustly identifying all sorts of vehicles and warning drivers about potential accident threat. However, it is challenging for vehicle identification due to huge variability in shape, color, and size of vehicles. Cluttered outdoor environment, illumination changes, random interaction between traffic participants, and crowded urban 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 related to vehicle speed. Higher the speed of vehicle less the time is available for processing a frame. Robustness must be fulfilled if the ego car is on urban road and where the accident probability is greater than on rural roads or highways. To design such intelligent systems, careful selection of sensors and detection algorithms is required.

Here, we provide discussion, critiques, and perspective on sensors, vehicle detection, tracking, motorcycle detection systems and nighttime vehicle detection.

A. 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 powerful computations. The long range detection (150 m approx.) of Radar based systems is more reliable in snow, foggy and rainy conditions 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 accuracy than radar. Systems designed using these high speed scanners are able to acquire shape and classify the target vehicle into car, bus, truck and motorcycle etc. Although providing useful information to CAS, laser scanner technology has not yet been introduced to commercial market due to its high cost, the associated processing unit, and driver software. On the other hand, radar and acoustic sensors collect less information about the target (e.g., shape, size, color etc.) and are more exposed to interference issues due to dynamic and noisy environment of road traffic. Noise removal and signal recovery may require complex 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 visual detection 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 [193] for 3D vision. Improved stereo matching 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, heavy computations of disparity map require high speed hardware for their real-time implementation. Fusion of sensors may make the system more robust and reliable as multiple sensors can extract maximum possible information from the environment. Fusion of active and passive sensors has achieved better results in terms of classification and robustness.

B. Analysis on Cueing Techniques

Motion based algorithms use relative motion of the objects to detect moving targets and require several frames for identification. Performance of such detection systems is affected by camera movement and may result in failure to identify objects with small relative motion (5 km/h) which is common in busy urban traffic [78]. Furthermore, these techniques have high computational load and may not be the best choice to fit in modern CAS as the onboard camera may vibrate while driving and vehicles on a highway have slow relative motion.

Techniques using symmetry, texture or corners features for HG are adequate in relatively simple environments but may produce several false positives in complex backgrounds [34], [84], [102]. Symmetry is an important clue, requires a rough guess for vehicle's position in an image and has relatively higher computational load than other appearance features. Therefore, it is time consuming and cannot fulfill the real-time operational needs of CAS, i.e., less than 100 ms or 10 fps. For example, in [85] the total detection time was up to 231 ms, while symmetry calculations already consumed 97 ms. It might also produce false detections due to presence of symmetrical objects in the background or during partial occlusion of vehicles. The texture technique can also produce several wrong detections particularly in a metropolitan area where the texture of roadside structures (e.g., sign boards, buildings or overhead passages) may be similar to that of a vehicle. The authors in [102] adopted fast wavelet transform and texture analysis the technique in a relative simple road situation (highway, i.e., less vehicles), but they did not demonstrate it in busy traffic areas. Meanwhile, multiple vehicles were detected using an adaptive model based classification with the same feature [101], but some vehicles were left undetected.

Object detection based on color characteristics is easily affected by intensity variation and reflective tendencies of the object. In open-air environments, different weather conditions and variation in illumination levels increase perplexity in vehicle detection. Detection rate had felt down to 75% due to illumination change [100]. This makes color feature along with texture and corner features, less desirable to be employed as appearance model.

Under normal circumstances, HG found by tracing shadow has been very successful [82] in terms of simplicity and high speed. The detection scheme might produce incorrect results during sunrise and evening time due to long shadows. This is because the location of shadows may not hypothesize the exact location of vehicles. It also fails when there are shadows of trees, poles and nearby buildings on the road surface. Furthermore, during night-time or bad weather, no shadows are cast that may cause this feature failure. Vehicle lights may be general features in darkness, but they do not work if these mix up with traffic lights, street lights, and other background luminosities.

Use of horizontal and vertical edges as features for HG is perhaps the most favorable method for practical perspective [83], [96] because of the rapid hardware implementations. One major challenge is the interference from outlier edges generated by background objects such as buildings, lamp posts or road dividers. Therefore, it is crucial to decide an optimal threshold to capture maximum edges of a vehicle with least possible edges from background. Moreover, specific parameters such as edge threshold values may perform well under certain situations but they might flop in other conditions. Multiple features have been recommended since they can provide more robust solutions and compensate the weakness of another. However, more computational resources are needed for calculating the additional cue that might be redundant.

C. Analysis on Verification Techniques

It is possible to skip the cueing stage and just use a verifier to scan for vehicles in the whole image, but it requires a high computational load. Template based methods are simple to verify the ROIs as vehicle or non-vehicle region but it is almost impossible to get a template that can fit all variants of vehicles. It is suggested to use a dynamic template that is able to accurately track different models of vehicles once it is correctly detected [137]. However, if there is false detection and a dynamic template is generated based on the wrong result, all subsequent tracking will also be wrong.

Learning and classification approaches have transitioned and have become more popular in recent years. Neural networks (NN) can deliver acceptable performance; their popularity in research communities has waned because their training features requires many parameters to tune and converge to a local optimum. Competing discriminative methods converge to a global optimum over the training set, which provides nice properties for further analysis, such as fitting posterior probabilities [42]. Quantitative results provided in Table III were initially reported by different researchers but we normalized them for our machine to have a fair comparison of the proposed methods. In our comparison, classifier based approaches are more accurate and closer to the real time requirements than motion based techniques. Statistics also show that SVM performs better than NN when trained on same dataset and tested for same targets. Right choice of features may also be advantageous to increase efficiency of a classifier. Another study [18] investigated PCA features, wavelet features, truncated/quantized wavelet features, Gabor features, and combined wavelet and Gabor features with NNs and SVMs in the context of vehicle detection. SVM classifications outperformed NNs in combination with all features and this is more prevalent in the modern vehicle literature [18], a trend which mirrors similar movement in machine learning (ML) and computer vision research groups.

Vehicle detection largely relies on ML approached, i.e., a feature extraction-classification paradigm. This approach works well when the vehicle is fully visible. In particular, robustly detecting partially occluded vehicles using monocular vision remains a challenge [194]. Classifier based verification methods are generally more accurate as compared to the template matching techniques [12], [18]. Many types of features and classification schemes proposed have shown their reasonable efficiency. Unfortunately, none of them can prove with full confidence in real-time situation.

D. Analysis on Tracking

Majority of existing on-road vehicle detection techniques [97], [98] use *detect-then-track* approach (i.e., vehicles are detected before being tracked). Although, it is possible to build a CAS without tracking by running and relying on detection schemes for each frame but integration of tracking with detection techniques is productive due to following reasons. First, the region for re-detecting a vehicle can be narrowed by exploiting the temporal coherence of video frames. Secondly, it can monitor the movement of a detected vehicle even though it is not momentary detected in one or several consecutive video frames. This will prevent the sudden ‘loss’ of a vehicle from the detection output due to occlusion or poor contrast between vehicle and road background.

Extended Kalman filtering for vehicle tracking has increased in popularity to accommodate the nonlinear observation and motion models [42], [183]. With the advancement and availability of fast computational machines, PFs are gaining popularity in tracking applications and dispensing some assumptions required for Kalman filtering [126]. Utilizing multiple models, however, seem to best account for the different modes exhibited by vehicle motion on the road.

E. Nighttime Detection

Most of the proposed systems for nighttime detection employed the brightness or vehicle lights as a clue [93], [139], but they suffer from distraction of street lights, lights outside shops and other bright regions. Some additional functions such as road brightness or day and night time detection can be added to allow CAS to automatically switch to the most appropriate algorithms for effective detection.

F. Analysis on Motorcycle Detection

Limited research has been conducted for motorcycle detection because of difficulty level and complexity in algorithm development. Separate detection and classification schemes [190] are required due to their wide ranges of shape and size. In most cases, the detection based on cameras is static, i.e., either it is mounted on a pole, roadside building or bridge for surveillance purposes. Therefore, it is easier to identify and track a motorcycle among the vehicles. However, the algorithms proposed in [97], [98] might fail to detect motorcycles during nighttime since the shadow information used is no longer applicable.

Appearance features had been applied successfully in vehicle detection systems [92], [93], [96] for car, truck, jeep etc., but in case of motorcycles, all of them failed to provide promising results. This is because it's small size which causes the measurement of symmetry property very difficult and not to provide actual ROI location. Use of color, corners, edges and texture characteristics also become ineffective due to variation in shape, size and color of motorcycle. In [97], shadow and black color feature showed positive results but the system may lose its robustness when motorcycle is far from camera or in different illumination conditions. Motorcycle detection by shadow detection is sensitive because they are always cast on either side. Furthermore, a classifier [142]–[145] requires a large set of motorcycle images to be trained on. The database should preferably have images with riders on the motorcycles because in the real world scenarios, the ROIs extracted contain similar instances.

We suggest a multisensory approach involving the use of camera along with an acoustic sensor to design a robust motorcycle detection system. In HG, shadow, tire and helmet detection might be useful in estimating the regions with ROI. In order to remove the displacement of ROIs due to side shadows, a position correction scheme must be used. In HV phase, a large database of motorcycle images will be required to train a classifier. From this review, we observe that SVM gave best result so it might be a better choice as classifier. Choice of features is crucial and different features need to be assessed to identify the most useful ones.

We also know that sound produced by motorcycle engine is characteristic and its frequency is different than that of other vehicles. Presence of motorcycle(s) can be predicted after filtering and applying signal processing techniques on acoustic signals obtained from road environment. By the fusion of image/video data and acoustic measurements, it is possible to build a reliable and real-time motorcycle detection system.

VI. Challenges

An important issue in the realization of a successful CAS is the design of vehicle detection systems with ultimate reliability and robustness in real-time. Considerable efforts have been made in this research area, several techniques and systems have already 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 through towards the development of autonomous vehicles equipped with modern sensors and CAS. This Google's fleet of robotic Toyota 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 success of a CAS will depend on the number of correct detections versus the number of false alarms. We have categorized the overall challenges into sensor challenges, algorithmic challenges and hardware challenges. We detail these challenges in following subsections.

A. 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 3D lidar scanner such as velodyne HDL-64E (see Table I). Price of 75k USD is more than the price of car itself and therefore CAS using 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 daytime 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 day and nighttime application of an inexpensive optical sensor. However, these sensors may have certain limitations such as narrow field of view. High resolution cameras with affordable price offer significant advantages by capturing fine details of road environments. On the other hand, high resolution leads to more data (pixels) to be processed causing an increase in processing time and requirement of powerful computational resources.

Vision-based systems and algorithms are yet to evolve into more powerful techniques to deal with busy and complex traffic situations. Fusion of multiple sensors could offer substantial improvements in CAS performance and it has the potential to yield a higher level of security and reliability (see Section II-C). 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.

B. Algorithmic 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 engine oscillations. This affects the orientation and alignment of the captured video and involves recalibration of camera. A practical CAS should remain unaffected and performance invariant in the presence of such vibrational noise. Moving camera also provides 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 identify vehicles 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-wheeled vehicles. In some countries (especially in ASEAN countries), a large number of motorcyclists appear on the road and their accident rate is higher than cars. There is a need of appearance clue(s) which can accommodate motorcycles along with other vehicles on road. In HV, more focus is on feature and classifier based validation using different training datasets. A wide range of feature extraction algorithms have emerged but efforts should be continued to determine the best features which can extract the maximum information from objects (vehicles) and widely separate them from non-vehicle class. Such features will allow classifier to recognize a target vehicle better and reduce the number of false alarms by increasing the efficiency. We believe 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). Furthermore, training and classifications are based on different data sets so comparison between these systems is difficult. This field is missing representative benchmarks for complete system evaluations and fair comparisons. It is also worthwhile to mention that efficient and powerful algorithms addressing the above mentioned challenges must be real-time since a small delay can make the whole CAS ineffective and unfeasible.

C. Hardware Challenges

On-board vehicle detection systems have high computational load as they must process the acquired data at real-time to save time for driver reaction. The real time implementation is also linked with relative speed between ego vehicle and the vehicle close to it. Greater the relative speed less is the time available for processing and driver reaction. Processing frequency should be higher than 15 Hz (15 fps) to meet the real-time requirements. Most low-level image processing techniques employed 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-time performance. With the drastic increase in computational power and speed of processors, we expect the availability of low cost and more powerful CPUs and GPUs for CAS in the near future.

VII. 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 are based 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.

VIII. 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 in different 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 to be 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 technology lacks motorcycle detection and classification of identified targets into car, truck, motorcycle, pedestrian, bicycle etc. These points need special consideration and work out for future CAS design.

Finally, this paper suggests a combination of optical sensors, appearance based cueing method and classifier based verification as the optimal choice for a low cost and reliable CAS design for vehicle industry.

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