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Vehicle Detection and Classification: A Review

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***Abstract*: Smart traffic and information systems require the collection of traffic data from respective sensors for regulation of traffic. In this regard, surveillance cameras have been installed in monitoring and control of traffic in the last few years. Several studies are carried out in video surveillance technologies using image processing techniques for traffic management. Video processing of a traffic data obtained through surveillance cameras is an instance of applications for advance cautioning or data extraction for real-time analysis of vehicles. This paper presents a detailed review of literature in vehicle detection and classification techniques and also discusses about the open challenges to be addressed in this area of research. It also reviews on various vehicle datasets used for evaluating the proposed techniques in various studies.**

Keywords: Intelligent transportation, Video Surveillance Technologies, Traffic Management, Vehicle classification, Traffic surveillance.

I. Introduction

Road accidents are the major cause of death for people between the ages of 5-29 worldwide. More than 1.35 million people lose their lives every year and 50 million are injured in road accidents [1]. India remains the world's number one for road crash fatalities since 2008. According to the Indian government, about 1.5 lakh people are killed each year by traffic accidents. These major challenges cannot be addressed only through traditional measures, including the expansion of existing transport infrastructure. Intelligent Transportation System (ITS) have been developed for the purpose of providing efficient services related to the different modes of transport and traffic management without embodying knowledge as such, allowing different users to be better informed and safer more organized and smart use of transport networks [2].

In order to plan, develop, run, implement and manage transport systems, ITS combines telecommunications, electronics and IT technology with transport engineering. The implementation of information and communicative systems in road transportation and their interfaces with other modes of transportation would make a significant variation in enhancing the quality of environment, efficiency in energy, road safety, transportation of dangerous goods, passenger and freight mobility [2].

Reports of vehicle accidents show that other vehicles pose the major threats to a driver. As a result, the development of on-board driver aided systems to warn a driver of driving environments and possible collisions with other vehicles attracted a great deal of attention [3]. The robust and reliable detection of vehicles is the first course of action for these systems. The identification and monitoring processes of vehicles include high-speed, low-speed, close-distance and self-driving. Over the last 15 years, significant attention has been paid to vision-based vehicle identification for driver assistance due to the dramatic loss in human lives and financial resulting from motor vehicle crashes, the availability of feasible technologies that have been accumulated over the past three decades from computer vision studies and the rapidly growing processor speeds.

In ITS, the vehicle type classification is of the utmost importance because it could be used for anomaly identification, counting, traffic breaches for specific vehicle types, etc. [4]. Contrary to typical classification problems, the classification task is classifying the objects within the same category as well as classify objects of different categories. The challenge in vehicle classification is to obtain adequate sensory information and the appropriate visual angle. The use of a stereovision method [5] will resolve these issues by permitting 3D information to be retrieved and the classification efficiency to be improved.

In recent years, stereo vision in the field of transportation has received great importance. It is employed to measure speed [6], rebuild the 3D view of vehicles [7], counting [8], detection and recognition of fine-grained models [9], Electronic Toll Collection (ETC) [10], smoky vehicle detection [11], detection of emergency vehicles [12] etc. Image-based vehicle target recognition is generally split between standard vision techniques and sophisticated methods of deep learning [8]. However, a local computing resource setting is often difficult to manage because of environmental conditions and installation in remote area in terms of vehicle identification and classification of ITS [13]. Some technology solutions recommend transfer of images collected by cameras to servers directly for the image processing, but this solution does not work since the device depends on the communication network and the related latency. In addition to this, the advancements in vehicle detection and classification is gradually slow due to non-availability of datasets and of which fine-grained vehicle models are highly similar [9]. We organize the rest of the paper as follows. Section 2, delivers the detailed review of recommended vehicle detection approaches available in the literature. Section 3, discusses about various vehicle classification techniques. Section 4, presents overall databases available. Section 5 briefly reviews about the open challenges and section 6 concludes the review of this article.

II. Methods used for Vehicle Detection

Two primary methods fall into the category of vision-based vehicle detection systems [3]: hypotheses generation (HG) and hypotheses verification (HV). The HG method identifies regions of the images that likely consist of vehicles with a quick analysis based on vehicle characteristics. The generated hypotheses are usually evaluated using machine learning techniques [14] in the hypotheses verification phase to further examine if the candidates are vehicles. As the HG stage's output is an input to HV, it is essential to ensure its accuracy in determining the regions of images with minimal false candidates.

Different approaches to HG have been suggested in [3] which can be grouped into three different categories based on knowledge, stereo, and motion. The HG stage aims to identify candidate car positions for further exploration quickly in a frame. Knowledge-based approaches use prior knowledge to infer that vehicle positions are depicted in a frame. Stereo-based methods are used to measure vehicle positions and obstacles in images by using the disparity map [15] and Inverse Perspective Mapping (IPM) [16]. Motion-based techniques use optical flow approach to track the vehicles and obstacles. The hypothesized sections which are generated in HG stage acts as an input to the HV stage.

A. Knowledge Based Methods

Knowledge-based approaches use information to estimate the positions of the vehicles in an image. Several descriptive methods using details like colors, symmetry, shadows, corners, texture, horizontal/vertical edges, structure and vehicle lights are listed below.

1) Color

In selecting a general vehicle detection feature, many problems and challenges will arise from diverse impacts of the environment, such as the weather, lighting or embedded background [17]. Although the colors of the vehicles are quite different, even at night the rear light in the picture is still red and color can be removed in real time. A pair of rear lights is contained in the suggested algorithm, and its symmetry-axis is a valuable indicator of narrowing down the search areas for potential vehicles. Three elements red, green and blue represent the color of an image captured by most charge-coupled device (CCD) cameras. These integrated components occupy an RGB (Red, Green, Blue)-color space [18] denoted as a three-dimensional space. In order to see that the red component is much larger than that of the green or blue element in the red region, we examine the RGB components of the color image.

Luo-Wei Tsai et al. [19] have introduced a color transformation model for converting all pixels with colors to a new dimension and assumed that N images were taken from various highways and parking spots. The covariance matrix Σ of R, G and B color distributions can be derived from these N images by statistical analysis. The eigenvectors and eigenvalues of Σ matrix can also be obtained and denoted as e_i and λ_I, correspondingly using the Karhunen-Loeve transform [20], for i = 1, 2, and 3. Then three new color features Ci, will be generated and named individually,

$$C_i = e_i^r R + e_i^g G + e_i^b B \quad \text{for} =1, 2, \text{and } 3 \tag{1}$$

where $ei = (e_i^r, e_i^g, e_i^b)$

The color feature C1 with the maximum eigenvalue is focused in the study of Ohta et al. [21], is

$$C_1 = \frac{1}{3} R + \frac{1}{3} G + \frac{1}{3} B. \tag{2}$$

Rojas et al. [22], have observed that the road colors along the axis guided by Eq (2) focus about the tiny cylinder. Based on this hypothesis, they have transformed all pixel colors on to a 2D color space to focus only on pixels of vehicles. By modeling this region of pixels, a Bayesian classifier [23] is trained to precisely estimate the vehicle pixels from backgrounds. Fig.1 illustrations the training set used in [19].

Figure 1. Training set. (a) Vehicle images (b) Non-vehicle images [14]

Video clips provide valuable information about colors that has been used to identify vehicle visual features like vehicle lights [24] and license plates [25]. Usually the surveillance cameras function with the RGB model, but there is a strong correlation among the three channels and values of each channel is largely dependent on brightness [26]. In order to resolve this issue, RGB color space conversion to HSV [27,28], YCrCb [29,30], L*a* b [31] is used to emphasize the color details in red and white and minimize illumination effect. A new color transformation technique for the recognition of vehicle color from static images was introduced in [32], to detect the vehicles with the help of Bayesian network. Husniza Razalli et al. [12] proposed a new visual analysis approach for the identification of an emergency vehicle by means of Hue Saturation and Value (HSV) color segmentation and support vector machine (SVM).

A new technique to identify and count the vehicles based on color space models has been implemented in [33]. This model uses color distortion and distortion in luminance of each pixel to identify the foreground pixels of the vehicle. The filtering approaches for eliminating noise are used in this work. While few prevailing systems use the full extent of the colour information for HG, this is an extremely useful hint for identifying obstacles, lanes and paths. Various studies have examined the use of colour details as a reference point for following roads [34], or segment vehicles from background [35,36]. In [34], to broaden a single camera's dynamic range, they have used two cameras; one for capturing the shadow field and the other to view the sunny area. They have built a six-dimensional color space model from the two pictures by merging their color information. This color space was represented by a Gaussian distribution, where the pixels were labeled as road or non-road.

For dark environments the most important preceding vehicle characteristics are rear-facing lights to detect the vehicles rather than shadows, horizontal and vertical edges and corners [37]. Rear lamps appear as the luminous areas in frames of a video at night; hence, for detecting of lamps some thresholding techniques like grayscale are used in image processing systems [38]. The resulting pixels are clustered and labeled for further analyzing the features, like shape and position of the region. Additional filtering is essential since several possible light emitting sources, like street lights, headlights of incoming vehicles and reflections from sign boards, along with rear vehicle lamps. The use of a red-color filter was observed as an efficient way to remove light sources of non-vehicles [37].

Several color spaces have been proposed for separating red-colored areas in the images with different parameters, but most of them are dependent on subjective color boundaries. Whereas the RGB color space is the most common approach, which is used in [39,40]. But it is hard to define and manage color parameters in RGB color space for thresholding [41]. The L*a*b color space was used in [42] to separate red vehicle lamps as it needs only two-color thresholding actions instead of three like the RGB color space and is therefore more computationally effective. Moreover, this leverage is rather ignored since the data must be converted into color space initially. The YCbCr space is used to determine the redness of the lights in [43] and analyzing the difference in red Chroma channel (Cr) to identify the bright areas which are leading sources of red lamps. Mallikarjun Anandhalli et al. [44] developed a system to detect vehicles based on the color features. The images are transformed from RGB to HSV color space in order to distinguish the vehicle colors. The HSV color image is divided into three channels and separately filtered to remove only the colors of the vehicle.

2) *Symmetry*

Symmetry, which is one of the major cues often used to identify human-made objects and recognize them in the computer vision [45]. Generally, vehicle images seem to be symmetrical from front or rear views, both horizontally and vertically. This hypothesis was used in many experiments as a guideline for vehicle detection [46,47]. Nevertheless, the existence of homogeneous regions is a significant issue when determining symmetry from intensity. Symmetry estimates are susceptible to noise in these regions. In [48], to filter out homogeneous areas, information on edging was used in analysis of symmetry. Seelen et al. [49] estimated symmetry with the help of neural networks in his work. The detection of vehicle position in images can be exploited by specifying the geometric model [50] which predicts the symmetry axes [51], or center points [52]. In combination with the symmetry operator, Khalid Zebbara et al. [53] suggested an approach that would identify certain obstacles on the roads, using the relation between the two successive frames.

Soo Siang Teoh et al. [52] proposed a monocular symmetry-based vehicle detection system which utilizes various image resolutions based on processing requirements. The initial stage is to identify the symmetry points of the picture at lesser resolution. The symmetry for an image is calculated to detect higher horizontal symmetry regions. In comparison to Bin et al. [54], have only performed symmetry calculations for various window sizes of each pixels along several lines of the scan. A different symmetry window size is used for each scanned line to detect symmetrical objects of different sizes. When it appears on the specific scan line in the image, the size was chosen to fit the most probable vehicle dimension. The symmetrical regions observed are then aggregated, and the mean points are assigned to each cluster for determining the position of possible vehicles. They have used another symmetry detection method which is based on contours and is quite sensitive to noise and variations in intensity. As this process doesn't require detailed picture information, the computations are minimized by a lower-resolution frame.

Ravi Kumar Satzoda et al. [55] suggested a technique incorporating an iterative window search algorithm integrating two parts to find fully visible vehicles using symmetry regression models in an iterative fashion. Another attribute that has been studied is the symmetry of fully visible vehicles in [56,57]. Nevertheless, today's video cameras are placed in distinct angles which make difficulty in using symmetry as a cue in hypothesis generation.

3) *Shadow*

The information related to the shadow of a vehicle was used as a cue for detection of vehicle for the first time in [58]. While examining the intensity of the image, the area below the vehicle was found to be noticeably darker compared to any other location on a road. An initial approach to use this feature is identified in [59], however the choice of acceptable threshold values was not taken in a systematic way. The intensity of shadow relies on the brightness of the picture, whereas it depends on the climatic conditions. Thus, it is difficult to set the threshold value. A lower and a higher thresholding process is required for segmentation of the shadow region. Through measuring the gray level of "free moving space," the higher thresholding can be determined. The same idea was adopted by Tzomakas and Seelen [60] and they proposed a procedure for determining the threshold values. In fact, the size of the free driving area was considered having a normal distribution. Using the maximum likelihood estimation, the mean and variance of the distribution are calculated.

One of the main challenges for vehicle detection is the identification of the shadow that the vehicle emits and its movement on the scene. When illumination varies, shadows can be the basis for various problems, like overlapping, deformation of the shape and missing of objects [61]. In many studies, for separating moving objects from shading background, they have used shadow analysis. Vehicle shadow area will typically be detected and extracted by creating a color model depending on contrast levels [62], luminance [63], mean and variation for altogether color components present in the scene [64]. The efficiency of vehicle detection algorithms can be significantly improved by means of shadow removal. Manuel Ibarra-Arenado et al. [65] have generated hypotheses by comparing pixel properties with vertical intensity gradients produced by shadows under vehicles, followed by intensity thresholding and morphological discrimination. Nur Shazwani A. et al. [66] have developed an algorithm to restrict the area of processing i.e. ROI in order to reduce the computational time. They have used horizontal Scharr-Sobel operator for improvement of edge features for vehicle shadow images. The connected component labeling algorithm is used for deciding the pixel region and direction by eliminating the noises like road sign, road marks, tress, etc. as they would reduce the vehicle detection accuracy. Finally, the shadow features are detected using blob analysis and acknowledging with the bounding box.

4) Corners

The truth is that automobiles are usually four-sided in rectangular shape (top-left, top-right, bottom-left and bottom-right). In order to detect the corners in a frame, four templates corresponding to the four corners are used and accompanied with a search algorithm to detect the corresponding corners [66]. Robert Kerwin C. Billones et al. [67] have used two algorithms for extraction of features using corner feature points in an image:

(a) Harris Algorithm

For the evaluation of corner selection criteria, the Harris corner detector [68] is determined for each pixel. If the criterion value is above a certain threshold value, the pixel is marked as a corner. For its estimation, the score uses two eigenvalues. The score is calculated with the following equations for the Harris corner detection (R is the score):

$$R = \det M - k\,(\operatorname{trace} M)^2 \tag{3}$$
$$\det M = \lambda_1 * \lambda_2 \tag{4}$$
$$\operatorname{trace} M = \lambda_1 + \lambda_2 \tag{5}$$

(b) Shi-Tomasi Algorithm

This algorithm is based on Harris corner detection algorithm. The selection criteria have a slight variation, which makes this detector different than the Harris‘s algorithm. In [69], they have proposed that the score should only be checked using eigenvalues values, in order to find out whether the pixel is corner.

M.D. Enjat Munajat et al. [70] have used corner detection process and the line adjacent detection features by creating black and white images through thresholding. The corners in the image are vibrant and strong in black and white mode with the use of the thresholding function. The threshold value is set to 30 for linking threshold and for upper thresholding they have consider up to 50. Then after thresholding the result is assigned to Kanade-Lucas-Tomasi algorithm for detection of corner spots and masked with the original image to observe the angle of detection [71]. Later the xy positions of individual corner spots are recorded and each corner spots are connected with straight lines. A filtering process is done to remove unnecessary lines by limiting the length of the line not exceeding vehicle’s length and leaving alone those lines which fall under the limit. The above process is demonstrated in figure 2. The dark/light values relating to those points is stored and processed for linking it to its environmental value. Yiqin Cao et al. [72] have developed an approach to address the occlusion issue in vehicle tracking using the optimized matching algorithm. They have stated that the proposed method decreases the computational complexity and improves the performance in real-time tracking by using gravity centre that is obtained through the corner points. At the same time, a minimum feature circle is created with all corner points, and the occlusion can be measured by the feature circle, thereby increasing tracking precision.

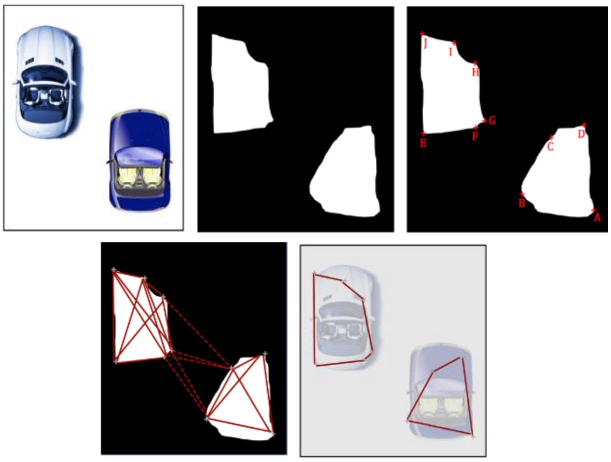

Figure 2. Vertex detection mechanism and Link between the vertices:

(a) location of car on road; (b) bright regions denoting the vehicles; (c) detected vertices for the bright regions; (d) connecting of vertices through lines; (e) filtering of unnecessary based on car’s length by convex-hull algorithm.

Naveen Chintalacheruvu et al. [73] used Harris-Stephen Corner detection algorithm to estimate the corners points and points of interest in the images using the deterministic interest point correspondence technique. The speed and number of vehicles are estimated depending on the location and positioning of interest points.

5) Texture

In terms of three-dimensional objects, texture analysis is treated as the best way in getting the details about it [74]. It comprises of sophisticated visual patterns and distinctive features like color, size, and brightness. For texture modeling there are different approaches like statistical models, transformational models and structural models. In [75], they have proposed that transformation methods allow spatial resolution variations to depict textures on various scales. Héctor A. Montes-Venegas et al. [76] have proposed two methods for vehicle detection using color and texture features. They have used L*u*v* color space [77] and the Dual-Tree Complex Wavelet Transform (DTCWT) [78] for texture and background modeling in the first method. The other method consists of change detection process which combines the variations in intensities and texture information among the current frame and formerly reconstructed background. They have also used L*u*v* color space and difference of texture measures which depends on the relation between gradients vectors. In order to estimate the background image, Lin et al. [79] used an auto -regression algorithm. Due to this, it is possible to directly separate dynamic images from the foregrounds by frame-difference. They have used Fast Wavelet Transform (FWT) algorithm [80] to extract the features like from the detected dynamic regions and Grey Level Co-Occurrence Matrix (GLCM) [81] to calculate and evaluate the extracted the extracted textures For segmenting of images on the basis of texture is proposed in [82] using co-occurrence matrices.

The cooccurrence matrix provides measures of the likelihood of pixel pairs occurring within the pre-defined geometrical and intensity limits. In texture analysis, the cooccurrence matrices usually give more accurate values than entropy technique as cooccurrence matrices do not use histogram information but rather second-order statistics as shown in figure 3. Indeed, it is expensive to calculate the cooccurrence matrices.

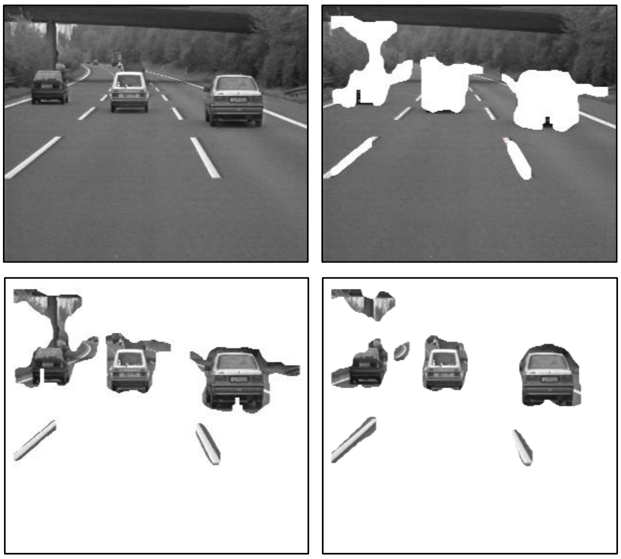

Figure 3. Segmented image based on entropy and co-occurrence [77].

M. Hassaballah et al. [83] proposed a vehicle detection method on the basis of pattern descriptors LBP which is a combination of appearance and texture information to represent the vehicle images. They have used a non-linear dimension reduction and clustering forests. If each region is matched to an individual histogram, the histogram is thresholded by calculation of Chi-Square dissimilarity that determines spatial clusters. A strong tree-structured detector is then developed using the salience map.

6) Vertical and Horizontal Edges

In particular rear/front views of a vehicle include various horizontal and vertical features like rear window, bumper etc. It has been a good indicator of the existence of vehicles using constellations with horizontal and vertical edges. Matthews et al. [84] have used edge detection technique to detect solid vertical edges in order to find distinctive vertical structures in an image. In order to determine the vehicle's left and right view, the vertical profile of the edge image was estimated using a triangular filter, accompanied by smoothing.

The Local Orientation Coding (LOC) system for the processing of edge information was introduced by Goerich et al. [85]. This approach consists of binary code strings that represent the directional gray-level difference in the pixel‘s neighbourhood. In [86], they have used LOC for vehicle identification, with shadow information. Parodi and Piccioli [87] have suggested the extraction of information from a traffic dataset by dividing each image onto four parts: the roadway, the sky and the two sideways. For the presence of vehicles, horizontal edge groups on the detected pavement were then examined.

M. Boumediene et al. [88] generated hypothesis based on detection of horizontal edges and limited the search area by using the Hough transform. In this method, a Sobel filter or a Canny filter is used to remove the contours and select the lines using Hough transform in the image where the search area is defined by those lines which is shown in figure 4. The hypothesis verification involves finding the "U" shape.

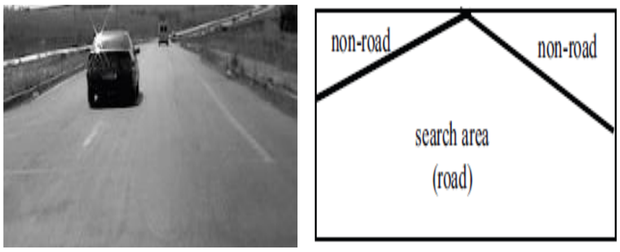

Figure 4. Delimited search area.

For this purpose, they examined the existence of two vertical edges (i.e. left, right) using Sobel filter, each of them linked to a horizontal edge which is detected during the hypothesis generation phase. Low level features can be easily extracted but the main disadvantage is that only one feature couldn’t provide useful information for efficient detection of vehicles. VanQuang Nguyena et al. [89] proposed an approach for vehicle detection which is relies on lane markings. Initially the image is filtered by horizontal edge technique and transformed to binary using the Otsu’s thresholding. Further, the image is subdivided into lane regions, depending on the lane markings. Whereas the Vehicles are detected using this information from the lane areas.

7) Vehicle Lights

Most of the above discussed approaches is of no use in the identification of vehicles at night. Shadows, horizontal/vertical lines, or corners would be challenging to detect in night-time pictures. The vehicle lights are an outstanding visual feature during the night. Cucchiara and Piccardi [90] used morphological operation in a limited inspection region to identify pair of vehicle lights. In order to generate hypotheses, the morphological operator examined the shape, size and distance between the vehicles. In the night time the brightness of lights in traffic images vary with the surroundings [91].

Jiann-Der Lee et al [92], have developed a vehicle lights detection technique by integrating the Laplacian of Gaussian (LoG) operator along with the diffusion light intensity mapping technique and the vehicle tail lights are tracked using optical flow method. They have used a mathematical model of a light source in determining the light intensities in the images, and the LoG operator to differentiate the lights among vehicles and non-vehicles. Chen et al. [93] developed a technique for segmenting the vehicles from traffic images taken during night time using the color variation and headlight information. The illumination caused by ground is removed from the object mask to attain good results.

In relation to this, information pertaining to headlights are used to measure the movement of vehicles rather than using a full vehicle structure. In [91], they proposed a technique in identifying the vehicles depending on the luminosity of the headlamps and taillights. Some of the night time images considered for vehicle detection is shown in figure 5.

Figure 5. Vehicle images taken during night time.

The arriving vehicles are distinguished by using National Television System Committee (NTSC) transformed image and the preceding vehicles are perceived using red-emphasized image. The blobs are spotted using Centre Surround Extremas (CenSurE) [94] from both the images. The blobs are observed by using the CenSurE from both the images with high speed using LOG operator. At the same time, the edges in the images are derived through zero-crossing of the CenSurE response.

B. Stereo Vision Based Methods

The stereo vision technique provides information of both depth and appearance to improve the detection accuracy. Disparity Map and Inverse Perspective Mapping (IPM) are two methods which uses stereo information for vehicle detection.

1) Disparity Map

Disparity gives us the information about the variations of the pixels among the left and right pictures. The inequalities of every point in the frame constitute the disparity map. The disparity map could be transformed to a 3D map of the traffic scene being viewed, if the stereo rig specifications are known. The processing of the disparities map takes a lot of time to solve the correspondence problem of each pixel; however, a Pentium class processor or an embedded hardware can be used to do so in real time [95]. Once the map of disparity is available, all pixels are calculated and summed in a histogram of disparity according to a depth of interest. Where there is an obstacle in the depth of interest, the peak in the respective histogram bin will occur. In [96] it was suggested that area-based techniques were computationally expensive to solve the correspondence problem and the disparity maps of feature-based methods were inadequate. To solve the correspondence problem more quickly, a local feature extractor was proposed. This method classifies each pixel into different categories on the basis of the variations in intensity between the pixel and its four immediate neighbors. The stereo-rig's optical axes are parallelly spaced to ease the search for pixel correspondences (i.e. points in each picture were on the same row).

For vehicle detection and the distance estimation depending on stereo vision, Djamila Dekkiche et al. [94] suggested a coarse to fine method. The method can be broken down into three stages of processing as shown in figure 6. The first step involves the processing of a detailed map of disparities which was recommended in [98].

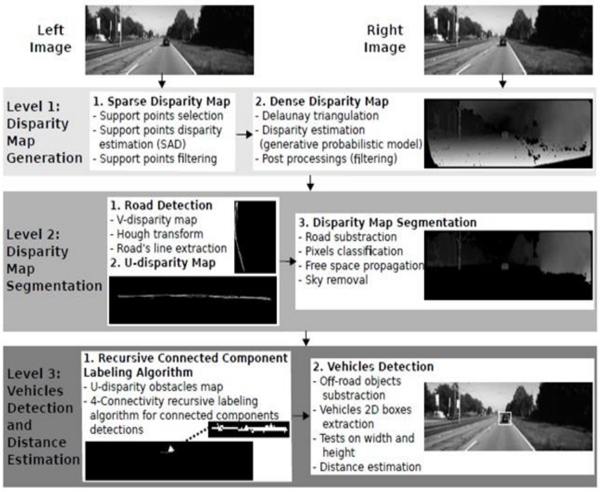

Figure 6. Algorithm's functional diagram

Second stage is segmentation based on the V-disparity map and a set of post-processing scene. The third level of vehicle detection is based on the U-disparity map formed by the disparity map for obstacles and the collection of post-processing tasks.

Wenhui Li et al. [99] has proposed a hybrid stereo vision method based on an algorithm in real time for vehicle detection. During the phase of hypothesis generation, one of the monocular images was used to extract the appearance features of vehicles. First of all, the reliable shadow features used to determine ROIs will be extracted. The semi-global stereo algorithm is used then to create maps with disparities. In the meantime, it is possible to obtain the distance and the actual width of the vehicles. Eventually, by clustering the noise ROIs with a greater variation in the disparity maps were omitted.

2) Inverse Perspective Mapping

Generally, the traffic scenes which are recorded by the surveillance camera is a projection of 3D coordinate system to the 2D coordinate system which is similar to a physical pinhole imaging model [100]. This method is mathematically called the Perspective Mapping (PM), while Inverse Perspective Mapping (IPM) is the reverse process. Instead the inversion shows that inverted points lie on the horizontal plane under the additional constraints [101].

When one considers a point p in 3D space, PM indicates that a line crossing the point and the projection center N as shown in figure 7. A line is passed through the plane of the image to find the image of the point. IPM process can be done in the following way: The ray through N to the horizontal plane is traced for a point of in the image. The ray intersection with the horizontal plane is the product of the inverse perspective mapping on the image point. The horizontal plane is mapped to itself as to combine together perspective and inverse perspective, but elevated sections of the region seem to be distorted.

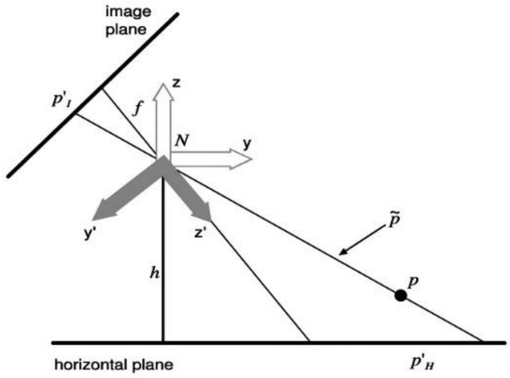

Figure 7. Geometry of perspective mapping.

Jong Bae Kim et al. [102] have introduced a method for the detection of an object and a method for measuring the distance of a vehicle from a bird's eye view using IPM. Thereafter, the maximum range between the detected vehicle and the autonomous vehicle was detected by IPM and by converting a 2D input image into 3D by generating a three-dimensional projected image. The identification and recognition of road markings is very difficult because of a perspective deformation in natural scenes. IPM is a widely used pre-processing method for specific road markings identification and classification to reduce the perspective effect [103], [104], [105]. In [106], an algorithm was suggested that addresses a general problem in the classical IPM, which is the interrupting the IPM image when there are obstacles in the way. The solution proposed is to connect the data from images with LRF data to determine in the picture the pixels that display the ground plane and must therefore be mapped by IPM.

C. Motion-Based Features

Automobiles are usually in motion, with ego and relative motion effects. In the absence of prior knowledge, the techniques separate moving vehicles from the background based on motion. Often the algorithms rely on sequences of image, whereas feature-based methods use static images. The vehicle detection techniques depending on the information of motion can be categorized into parametric methods and non-parametric.

1) Non-parametric Methods

The easiest method of motion detection is non-parametric models. These techniques detach the foreground from the background in a pixel-by-pixel approach without any conditions. In earlier, the frame separation [107,108] is a commonly used approach for moving vehicle identification. The conventional two-frame difference approach looks at the difference between two images [109]. The disparity image map is attained by separating the existing frame I_n from the preceding frame I_{n-1}. Thresholding is done to segment the foreground from background by considering pixel values greater than the threshold value to be foreground. This approach can produce disparity maps in real time, but is subject to changes in illumination. The key limitations in frame differencing method is the presence of gaps in the segmented objects as they keep moving gradually and the ghosts following the segmented parts [110]. In [111], a solution was given to detect slow-moving vehicles, where frame In and I_{n+5} were chosen to build binary disparity maps instead of two consecutive frames. Nevertheless, the contour information produced by two image frames overlap as vehicles move quickly in video clips. So, a three-frame difference approach was used in [112]. Using three video frames two disparity image maps were obtained. In order to fill the gaps and join the discontinuities, morphologic operations (i.e. difference, dilate, AND and XOR) are performed.

In dynamic urban traffic environments, the subtraction background model is quickly filled with slow moving or temporarily stopped vehicles. Yunsheng Zhang et al. [113] suggested a nonparametric approach with confidence measurement for identification of vehicles in urban traffic clips. They also used a traffic flow evaluation scheme as in Sigma-delta with confidence measurement (SCM) [114,115] and the same background model and foreground decision rule as in Visual Background extractor (ViBe) [116]. The background model is calculated for all pixels detected recently and a collection of pixel values recently measured during a specified time period determines an initial background model for each pixel. Then, for the preliminary background model, the confidence time, named confidence measurements is defined for each pixel and the current pixel value is equated to the values of the background model in order to decide the pixels belonging to the foreground/background model. The traffic flow states are then analyzed to decide if the background model is to be modified over the confidence phase. The consistency and durability of the present location is measured at the end of the confidence period to modify the decision threshold and also traffic flow states to attain the confidence period and decide if it is appropriate to update the background model.

2) Parametric Methods

Parameter methods like optical flow and background modeling are discussed in this section.

(a) Background Modelling

The background is considered to be motionless and any object with a particular movement can be assumed to be part of foreground. Background modeling will address three questions, according to: 1) What is the model and how would it act? 2) How does the model gets initialized 3) How is the model gets updated?. The algorithms for background modeling generally consist of initialization of the background, detection of foreground and updating of background.

Stauffer and Grimson [117] have developed the Gaussian mixture model (GMM), which is the most common background modeling approach for moving objects. They have stated that a combination of finite Gaussian distributions with undefined variables produces all data points. The GMM method uses multiple and adaptive Gaussians to model each pixel and uses an online approach to keep updating the model. There are two parameters, i.e. the learning rate and the threshold are essential for this model. GMM needs three Gaussian possibilities and three comparative operations for the model matching process. GMM needs one Gaussian possibility, eight multiplication, and four subtraction operations to be implemented in updating the model [118]. The adaptive GMM background subtraction method was enhanced in [119] which deals with pixel-level. This method is able to automatically identify the desired number of components and constantly update the necessary number of components so that processing time is reduced. The generalized model is defined as the region-based combination of Gaussians, which was introduced in [120] by expanding the conventional pixel-based mixture model to neighborhood areas.

According to earlier studies, the background subtraction model is suggested as the suitable solution for vehicle detection through still cameras. A new, modified model for subtracting backgrounds was developed in [121] which appears to be working to tracking in real-time and shadow detection. After the background subtraction, a component labeling method is used to label the various objects so that the two objects can be differentiated and each region is labeled.

(b) Optical Flow

The distribution of velocity patterns of the moving objects in a frame is analyzed through optical flow technique. The relative movement of objects and viewers can result in optical flow. It gives more amount of information related to the position of the objects and their frequency of moving [122]. Basically, optical flow analysis is done in two stages:

a) Evaluation of spatio-temporal intensity derivatives

b) Integration of normal velocities into full velocities

The vehicle motion is perceived and tracked by optical flow algorithm [123] along the frames. The distance covered by the vehicle is estimated by shifting of the centroid over the frames and by calculating the speed of the vehicle. Using Pyramidal optical flow estimation and a morphological transformation operator, the moving vehicles are detected in [124]. Kuo, Y. C et al. [125] proposed a refined image processing algorithm to achieve vehicle front features and the optical flow method was then used for vehicle tracking. Based upon the optical flow estimate on the edge image, Yanfeng Chen et al. [126] developed the moving vehicle detection algorithm. The Canny operator is used to attain the edge image which is then refined and transformed to a set of feature points. Then the Lucas-Kanade optical flow model [127] is used to calculate the optical flow data of the feature points. Eventually, the weighted K-means optical flow clustering algorithm [128] is used to detect the moving vehicles.

Work	**Detection Technique**	**Data Set**	**Accuracy (%)**
Luo-Wei Tsai et al. [19]	Colors and Edges	Own dataset	94.5
Soo Siang Teoh et al. [53]	Multi-Sized Window and Clustering Technique	Own dataset	94.6
Ravi Kumar Satzoda et al. [55]	Haar-Like Features and Adaboost Classifiers	Motor way Datasets	87
Manuel Ibarra-Arenado et al. [65]	Intensity Thresholding and Morphological Discrimina-tion	Caltech dataset	98.04
Robert Kerwin C.Billones et al. [67]	Harris corner detection, Shi-Tomasi corner detection	CBCL	90.30
Hassaballah M. et al. [83]	LBP Descriptors + Tree-Structured Detector	UIUC Dataset	99
Boumediene M. et al. [88]	Horizontal/Vertical Edge Detection Algorithm	Own dataset	90
Wenhui Li et al. [99]	Semi-Global Matching Algorithm + Histogram of Oriented Gradient (HOG) Feature	KITTI Vision Benchm-ark Suite	95.59
Ahmad Arinaldi et al. [143]	MoG + SVM	MIT Traffic	69.4

Table 1. Vehicle Detection Approaches in various works.

The comparison of various detections methods explored in this review are shown in figure 8 for the respective dataset. As there is very less research work done in this area and no standard dataset is available, we are not able to provide the comparative analysis for various techniques.

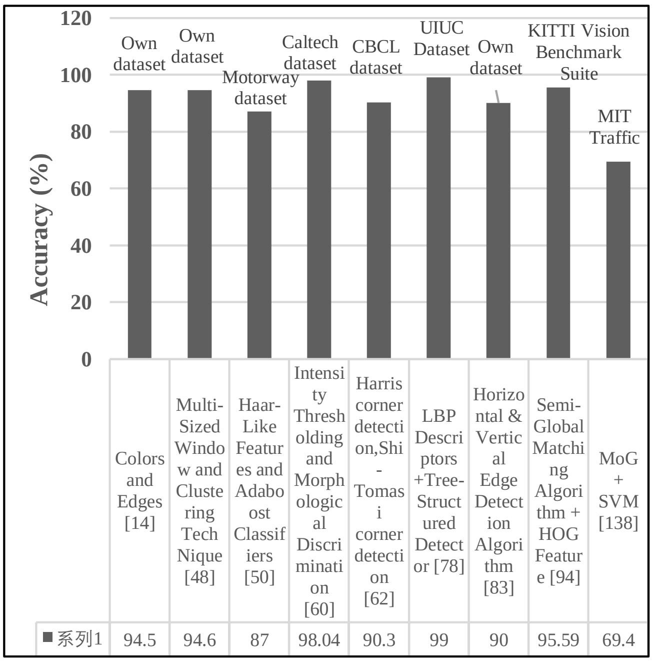

Figure 8. Comparison of various detection methods.

III. Hypothesis Verification (HV)

The next step is to test the validity of the hypothesis after extracting possible candidates out of the image sequences. Hypothesis Verification (HV) is viewed as a two-class pattern classification problem using the machine learning: vehicle versus non-vehicle. Firstly, the classifiers are trained with the positive images (class of vehicles) and negative images (not car class) collected from various sources. All training samples have one or more feature vectors for each image. Classifiers learn statistically the features of the appearance of vehicles and differentiate between vehicle classes. For optimum appearance-based classification efficiency, it is important to discard enormous within class variations.

A. Template-Based Methods

Template-based approaches employ vehicle type pre-defined patterns and correlate the image with the template. Parodi and Piccioli [129] have proposed an HV method depending on the detection of the vehicle's license plates and rear windows. Handmann et al. [130] suggested a template-based model on finding that a vehicle has "U" shape on its front/rear view. They assumed a vehicle was present in the image when the "U" shape was identified during hypothesis verification. Active sensors were used for HG by Ito et al. [131] to verify edges (i.e. vertical or horizontal) and symmetry existed. In order to detect preceding vehicles (front and behind view), Nima Khairdoost et al. [132] have generated hypothesis with three indicators (i.e. entropy, symmetry and shadow) without any prior information about the location of the road. They have done a four-stage hypothesis verification process, first Pyramid Histograms of Oriented Gradients (PHOG) features generated from the image dataset along with the image obtained by filtering through the Gaussian filter are considered as the primary features. Secondly, they used Principal Component Analysis (PCA) to minimize the PHOG descriptor dimensionality and to achieve minimized PHOG-PCA features. In order to achieve better performance and generalization, they eventually used Genetic Algorithm to find the best weights for these features in terms of classification accuracy and the total features used.

In the process of hypothesis generation, Abdelmoghit Zaarane et al. [133] have firstly determined position of potential vehicles using the cross-correlation technique of template matching. In the second stage, the two-dimensional discrete wavelet transformation (2D-DWT) is used in the extraction and classification of features from the generated hypotheses. For HV process they have used SVMs and AdaBoost classifiers.

B. Appearance Methods

The development of a comprehensive classification system requires a quest for an optimum boundary for class decisions. The sensible solution is to know the decision-making system on the basis of classifier that has been trained using the feature set. The appearances of the vehicle will be learned and the variations in the vehicle classes are recorded from the training dataset. Initially, a set of training images are collected and the local/global features are represented for all the training dataset. By training the classifier for each class, the decision boundary among the vehicle and the non-vehicle classes can be determined. The difficulty in extraction of global features in local or global images is that they seem to be sensitive to the changes like position, illumination, and partial occlusion. On the other hand, local feature extraction methods are less vulnerable to such effects. In addition, structural details and constraints can be used explicitly or implicitly in the design of various local features. In conjunction with the nearest neighbor classifier, Wu and Zhang [134] used the PCA for feature extraction. Minkyu Cheon et al. [135] have proposed a method using the knowledge-based HG process that uses shadow regions to extract hypotheses. In HV, the system utilizes the histogram of oriented gradients (HOG) [136,137] and HOG symmetry vectors [138] for representation of feature vectors and Total Error Rate Minimization Using Reduced Model (TER-RM) [139] for classification. A new strategy for vehicle detection has been developed by Daniel Alonso et al. [140] focused on classifying metrics of multidimensional probability. A feature vector is tested for the candidate sub-regions of the images comprising of vehicles which leads to classification of vehicle or non-vehicle classes. This technique is focused on minimizing Mahalanobis distance in representation of feature vectors and vehicle classes attained through a supervised learning process.

Zehang Sun et al. [141] have designed and developed a monocular road detection model using the low-light Ford camera in real time. They have used multi-scale hypothesis generation method and appearance-based technique for verification of hypothesis. The generation of multi-scale driven hypotheses leads to possible hypotheses with reasonable information. In HV phase, the appearance-based model validates the hypotheses using Haar Wavelet features and SVMs. Zebbara Khalid et al. [142] have decided the presence of vehicles on the basis of present and previous frame. They used the method of association to define the relation between consecutive frames. This method exploits the displacement of edges in the frames. The Adaboost classifier is used to assess whether an obstacle is a vehicle.

Ahmad Arinaldi et al. [143] introduced a system that automatically calculated the number of vehicles, classifies vehicles by type, measures the speed and decides the lane usage. In order to achieve this, they have implemented and compared two systems: one system comprising background modeling using Mixture of Gaussians (MoG) for foreground detection and SVM classifier for classification of vehicles and another system based on the Faster RCNN. However, they reported that the Faster RCNN algorithm performs better in dynamic traffic scenes. Yu Wang et al. [144], have developed a system for detection and classification of moving vehicles termed as Improved Spatio-Temporal Sample Consensus. Firstly, the moving vehicles are identified using Spatio-Temporal Sample Consensus algorithm, from the intrusion of brightness variation and the vehicles shadow. Furthermore, by means of feature fusion techniques the objects are classified according to area, face, number plate and vehicle symmetry features.

Chia-Chi Tsai et al. [145], proposed an optimized Convolutional Neural Network architecture based on deep learning algorithms for vehicle detection and classification system used for intelligent transportation applications. PVANET [146] as the base network, is selected and improved by fine-tuning to get better accuracy. It consists of eight Concatenated ReLU convolution layers and eight inception layers for the base network. The hypernet architecture is used to associate dissimilar features, thereby making it better to achieve the desired bounding boxes for the Region Proposal Net layer.

In [147], they have presented a model based on vision analysis with a fixed camera for monitoring the traffic, detection of vehicle that includes occlusion handling, counting, tracking and classification. Murugan and Vijaykumar [148], have developed Adaptive Neuro Fuzzy Inference System classifier for classification of moving vehicles on the roads. It includes six main phases like pre-processing, feature extraction, detection, structural matching, tracking, and classification of vehicles. A background subtraction and the Otsu threshold algorithm are used for vehicular detection. The characteristics of the vehicles detected are obtained by the log Gabor filter and Harris corner detector, which are used to classify the vehicles.

Audebert. et al. [149] have conferred a segment before detect approach using deep learning techniques. Segmentation and followed by detection and classification of multiple wheeled vehicle variants is tested for high-resolution remote sensing pictures. The detection and classification of vehicles depending on a virtual detection zone was suggested in [150], which comprises of foreground extraction, detection, feature extraction and classification. The GMM is used in detection of vehicles and also some operations are performed to get the foreground objects and classification is done, using k-nearest neighbor classifier. In [151], they have recommended a semi-supervised convolutional neural network technique for vehicles classification based on front view of vehicle. Yet, the features trained by the CNN are too biased to work in raster images. Banu et al. [152] have recommended Histogram of Gradient feature extraction technique and morphological operations for better detection rate. Comparison of different approaches for Vehicle classification and their success rate are shown in Table 2.

Work	**Approach**	**Dataset**	**Classification success rate (%)**
Luo-Wei Ts al. [19]	Gaussian Model	Own Dataset	94.5
Ravi Kumar Satzoda et al. [55]	Haar-Like Features and Adaboost Classifier	Motorway Dataset	87
Manuel Ibarra-Arenado et al. [65]	Support Vector Machine	Own dataset	98.04; 97.71
Robert Kerwin C.Billones et al. [67]	Harris-ANN, Shi-Tomasi - ANN and FAST-ANN	CBCL	90.30
Wenhui Li et al. [99]	Support Vector Machine	KITTI Vision Benchmark Suite	95.59
Ahmad Arinaldi et al. [143]	MoG + SVM, Faster RCNN	Indonesian Toll Road, MIT Traffic	54.5; 67.2
Yu Wang et al. [144]	Improved Spatio-Temporal Sample Consensus Algorithm	CDnet 2014, MIO-TCD, and BIT Vehicle	97.8
Chia-Chi Tsai et al. [145]	Chia-Chi Tsai et al.	IVS-1&2	90
Roxana Velazquez-Pupo et al. [147]	OC-SVM	GRAM-RTM, M6 motorway	99.05
Murugan and Vijaykumar [148]	Adaptive Neuro Fuzzy Inference System classifier	Own Dataset	92.56
Nicolas Audebert et al. [149]	Convolutional Neural Network	ISPRS Potsdam dataset, NZAM/ ONERA Christchurch Dataset	67; 80

Table 2. Summary of Classification Approaches

The classification techniques explored in this literature are compared and shown in figure 9 for the respective dataset. As there is very less research work done in this area and also no standard dataset is available for evaluation of all the techniques, we are not able to provide the comparative analysis for various methods.

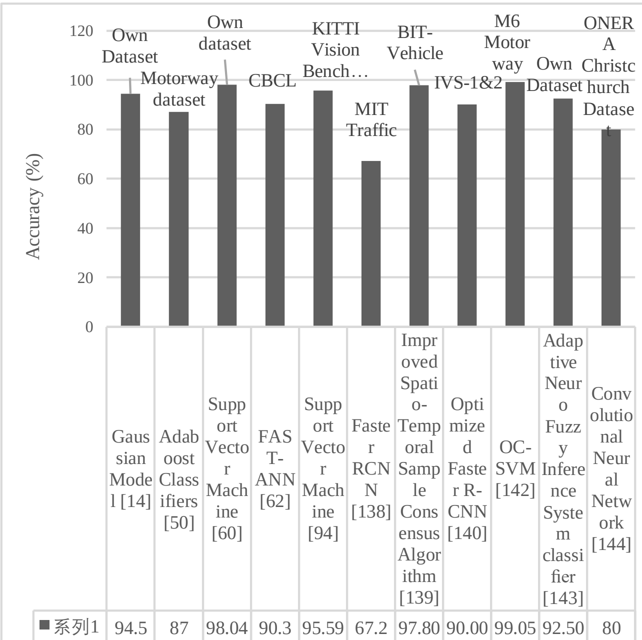

Figure 9. Comparison of various classification methods

IV. Database

The surveillance cameras installed on the roadways in almost all the countries is growing rapidly. The images obtained through these cameras are maintained by departments of traffic control. As a result, few traffic analysis data sets were made public. The data sets that are most widely used can be classified into three groups, namely: (1) data sets obtained through onboard cameras which are primarily aimed for self-driving cars, (2) datasets collected by non-surveillance cameras (3) datasets captured by surveillance cameras. A concise overview of existing vehicle detection and localization databases is provided here.

A. KITTI Vision Benchmark Suite [153]

A broad dataset provided by an autonomous driving platform is the KITTI Vision Benchmark Suite which addresses various challenges in the real world like 3D object detection, tracking of 3D objects, optical flow estimation, stereo vision calculation, visual odometry/SLAM. The data set includes video clips recorded from cars on highways and smaller towns.

B. Cityscapes Dataset [154]

The Cityscapes dataset rests on the semantiquely segmented urban road views. This dataset includes a diverse collection of street scenes of high quality, 5000 full-length pictures and 20000 weakly marked pictures, including stereo videos taped from 50 different cities in street scenes. Only photos taken during the summer and in urban areas in 50 cities are available.

C. Tsinghua-Tencent Traffic-Sign Dataset [155]

It is a huge data set with 100,000 pictures and 30,000 instances of road traffic signs. Images in this dataset cover different lighting and climatic conditions without including any labeling.

D. Stanford Car Dataset [156]

The Stanford Car dataset includes 16,185 vehicle pictures in high resolution of 196 classes with manufacturer; model and year (e.g. “AM General Hummer SUV 2000”, “Chevrolet TrailBlazer SS 2009”) are included. This data set consists of 8144 car images for training and 8041 car images for testing. All images are of great resolution and captured with a large range of vehicles in perfect lighting environments. Indeed, the images were not captured in a top down angle, as in the case of surveillance cameras.

E. Comprehensive Cars Dataset (web) [157]

It's one of the biggest car datasets available today which includes 136,727 pictures with complete cars and 27,618 pictures with car parts. It contains 1,716 car models with five attributes (i.e. speed, displacement, available of doors and seats, and types of car). The same drawbacks as Stanford Car Dataset are also found in this dataset, i.e. images captured are dissimilar to that of a surveillance camera.

F. Comprehensive Cars Dataset (surveillance) [157]

The Comprehensive cars dataset includes 44,481 images of the front view of cars taken by surveillance cameras. The ground truth is provided in this dataset which gives each vehicle its color and model. In contains frontal view of the images, making it difficult to categorize it to a specific camera position. In comparison, this dataset focused only on cars, pickup trucks and minivans, and does not include motorcycles, pedestrians, cyclists and large vehicles like trucks and buses.

G. BIT-Vehicle Dataset [151]

The main disadvantage of the BIT-Vehicle dataset has 9,850 vehicle images captured through monitoring cameras which is one of the most realistic datasets. The vehicles are classified as six classes, namely buses, micro busses, minivans, sedans, SUvs and trucks. Inappropriately, all these images were taken at the top front view during daylight and good weather, thereby reducing the homogeneity required for the analysis of traffic.

H. Traffic and Congestions Dataset [158]:

The uniqueness in this dataset is that it can be helpful to determine the vehicles, that are intensely congested on highways. There consists of 1,244 images captured by surveillance cameras, which were mostly occluded with 46,796 labeled vehicles in this dataset. The vehicle type or other details were not specified which is a drawback in this dataset.

I. GRAM Road-Traffic Monitoring Dataset [159]:

There are very few standard datasets available for evaluation of tracking of multiple vehicles, where this would serve the purpose to some extent. It includes video clips recorded under various conditions and on multiple platforms by surveillance cameras. Each vehicle was annotated manually in various categories like car, van, truck, and large truck. Nearly, 240 different objects are present in each video clip of this dataset.

V. Open Challenges

The effectiveness of a road detection system from a technical point of view would reflect on the number of successful detections against the number of negative detections it generates, provided with necessary framework. It is not easy to achieve the optimal level of accuracy for vehicle detection which would also depend on the complexity of the application. For comparison, adaptive vehicle control systems must be more selective when it comes to false alarms. There are several approaches by which false positives can be substantially reduced while maintaining high precision including enhanced algorithmic solutions like using multiple cues, learning models and advanced statistical methods, sensors fusion and telematics like vehicle-to-Vehicle communication and GPS-based localization. Further we will discuss these issues in more depth.

A. Occlusion Effects

It might be one of the foremost challenges yet to be resolved. More work needs to be done in this field, in order to develop reliable systems for pedestrians, cyclists, other vehicles, and so on for marginal or severe occlusions.

B. Customized Vehicles

As per the literature done until now, no research work is published related to classification of modified vehicles, where the original model might be customized by the owner in terms of appearance, shape, or design.

C. Benchmark Dataset

Our analysis reveals that a standardized benchmark dataset is not available for public usage to develop various techniques. So, there is a need for a dataset which addresses most of the real time on road traffic issues.

D. 3D AVC

We found no list of works reported about using 3D cameras and 3D vehicle datasets. Instead many works were published by projecting 2D image onto 3D.

E. Multi-lane AVC

Many of the works analyzed presume that one vehicle per lane, or one vehicle per input image. The development of comprehensive and simultaneous vehicle classifications in multi-lane conditions is an area to be explored.

F. Multi-target Recognition

One would need a classification system for multiple targets (i.e. pedestrians, vehicles) in an urban area. While systems have been developed in detecting pedestrians and vehicles independently. So, we still have to see robust automatic detection systems to accomplish these objectives.

G. Online Testing

Many authors use still photographs taken from video clips to validate their methods through offline testing. So, there is a necessity for developing platforms for Online testing of live images.

H. Multi-modal Sensing

Though the majority of works we discussed in this review are exclusively based on vision sensors, vehicle detection and classification system might benefit from the integration of vision sensors and as well as other sensors to address limitations.

I. Vehicle Make, Model and Generation Recognition

Comparatively a less explored field of study is the classification of different kind of company specific manufactured vehicles and their models. So, there is need for development of systems for classification of various classes of vehicles which would benefit the traffic management related applications.

VI. Conclusion

In this paper, a detailed overview of literature on video-based traffic monitoring and classification systems using computer vision methods is presented. The purpose of this study is to support the researcher in the detection, classification and availability of car data sets of vehicles. The most prevalent issues in this field are the biased form of datasets and the distinct vehicle types with the same size and form, which makes it more difficult to categorize them. There are various open challenges to be addressed which are discussed in this article.

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