Accepted Manuscript

Vehicle Detection in Intelligent Transportation Systems and its Applications under Varying Environments: A Review

Zi Yang, Lilian S.C. Pun-Cheng

PII: S0262-8856(17)30159-2
DOI: doi:10.1016/j.imavis.2017.09.008
Reference: IMAVIS 3652

To appear in: *Image and Vision Computing*

Received date: 29 November 2016
Revised date: 4 July 2017
Accepted date: 28 September 2017

Please cite this article as: Zi Yang, Lilian S.C. Pun-Cheng, Vehicle Detection in Intelligent Transportation Systems and its Applications under Varying Environments: A Review, *Image and Vision Computing* (2017), doi:10.1016/j.imavis.2017.09.008

Vehicle Detection in Intelligent Transportation Systems and its Applications under Varying Environments: A Review

Zi Yang [a, *], Lilian S. C. Pun-Cheng [b]

[a, b] The Department of Land Surveying and Geo-Informatics,

The Hong Kong Polytechnic University, Hong Kong

[a] 15900778r@connect.polyu.hk; [b] lspun@polyu.edu.hk

ABSTRACT

Robust and efficient vehicle detection in monocular vision is an important task in Intelligent Transportation Systems. With the development of computer vision techniques and consequent accessibility of video image data, new applications have been enabled to on-road vehicle detection algorithms. This paper provides a review of the literature in vehicle detection under varying environments. Due to the variability of on-road driving environments, vehicle detection may face different problems and challenges. Therefore, many approaches have been proposed, and can be categorized as appearance-based methods and motion-based methods. In addition, special illumination, weather and driving scenarios are discussed in terms of methodology and quantitative evaluation. In the future, efforts should be focused on robust vehicle detection approaches for various on-road conditions.

Keywords: Vehicle Detection, Computer Vision, Intelligent Transportation Systems, Varying Environments, Traffic Surveillance

1 Introduction

Intelligent Transport Systems (ITS) is a popular field of research in recent years. By providing innovative services relating to different modes of transport and traffic management and enabling various users to be better informed and make safer, more coordinated and 'smarter' use of transport networks [110], ITS aims to improve transportation safety, mobility, productivity and environmental performance for traffic planners and road users. With continuous urban road development and extensive construction of expressways, increasing interest is devoted to vehicle detection. As an essential task in ITS, vehicle detection aims to provide information assisting vehicle counting, vehicle speed measurement, identification of traffic accidents, traffic flow prediction, etc.

There are various sensors used to collect continuously-generated traffic information. Traditional approaches utilize dedicated hardware [49] such as inductive loop detectors, radar detectors, laser detectors to detect vehicles, but the main drawbacks of these equipment are high maintenance cost and being affected by environmental factors. Comparing to traditional sensors, video cameras are more advantageous in terms of cost and flexibility. Video cameras have been deployed for traffic surveillance for a long time, because they provide a rich contextual information for human visualization and understanding. With the increasing numbers and coverage of CCTV cameras and consequent accessibility of image data, image-based vehicle detection is one of the most promising new techniques for large scale traffic information data collection and analysis [7]. In recent years, there is even a trend to fuse data from different sources [71] to detect vehicles.

To be useful, vehicle detection methods need to be fast enough to operate in real-time, be insensitive to illumination change and different weather conditions, and be able to separate vehicles from images sequences in an accurate and efficient manner [65]. Under various driving conditions, vehicle detection methods have been reported in the literature [2, 3, 4, 5]. Many of them focus mainly on algorithms and technologies, while the application domain is seldom summarized. In this paper, we provide a review of vehicle detection approaches under varying environments. We categorize vehicle detection methods based on vehicle appearance and vehicle motion. Then, we summarize several traffic surveillance objectives, such as vehicle counting and detection of traffic accidents. We put our focus on vehicle detection under special illumination and adverse weather scenarios. Solutions under varying environments are compared and evaluated for different vehicle detection purposes.

2 Vehicle Detection - Appearance-based Methods

Appearances of vehicles vary in size, shape and color. In vehicle detection, appearance-based methods employ prior knowledge to segment foreground (contains the objects of interest) and the background (its complementary set) [22]. Due to the rectangular shape of vehicles, various features serve as important cues for vehicle detection, such as symmetry, color, edge (horizontal/vertical), shadow. Each feature has its own advantages and weakness, and can be used singularly or in combination. Based on these features, descriptors have been proposed and proved to be effective in vehicle detection. According to [27, 37], appearance-based vehicle detection methods often follow two basic steps: 1) hypothesis generation (HG) where the locations of possible vehicles in an image are hypothesized, and 2) hypothesis verification (HV), where tests are performed to verify the presence of vehicles in an image.

2.1 Hypothesis Generation (HG)

Low-level Features

Here we review representative low-level features e.g., color, shadow, symmetry and edge, for the use of appearance-based HG. These features are simple, efficient, and of great usefulness in vehicle-related information extraction.

a) Color: Color information provides rich information in video images, and has been utilized to detect visual features of vehicles such as vehicle lights [38], license plates [107]. Traffic surveillance cameras often operate with the RGB model, but the three channels are highly correlated and the individual value of R, G, B depends on brightness strongly [24]. To solve this problem, conversion from RGB color space to HSV [26, 34], YCrCb [8, 35], L*a*b [31] is operated to highlight the red and white color information and reduce the effect of illumination change. In [7], a new color transformation model was proposed to identify vehicle color from static images. Table 1 shows how color information is utilized in vehicle lights detection.

Table 1. The use of color in vehicle lights detection

Reference	Color Space	Corresponding component in RGB color space	Application
[29]	RGB	Red	Tail-light detection at night
[26]	HSV	Red	Tail-light detection at night
[34]	HSV	Red and White	Tail-light detection at night
[35]	YCrCb	Red	Tail-light detection at night
[8]	YCrCb	Red	Brake-light detection at daytime
[30]	L*a*b	Red	Tail-light detection at daytime/adverse weather conditions
[32]	L*a*b	Red	Brake light detection at daytime

b) Shadow: For vehicle detection, one of the main challenges is identifying a shadow which vehicle casts and its movement in the scene. As one kind of local illumination changes, shadow may cause many problems such as merging, shape distortion and a loss of objects [79]. By distinguishing shading background from moving objects, shadow analysis is an active research area in many studies [85]. Generally, vehicle shadow region can be identified and removed by building a color model based on contrast [106], brightness [80], mean and variance of all color components [86]. With the help of shadow elimination, performances of vehicle detection algorithms can be improved significantly.

c) Symmetry: From the frontal or rear view, images of vehicles usually have symmetry property. Symmetry has been used as a cue for vehicle detection in some early studies, see [13, 14]. It is often utilized by defining a geometric model [15], finding symmetry axes [16] or center points [17] to identify the vehicle location in images. However, current video cameras are installed at locations with different angles and views, making symmetry a less-used feature in state-of-the-art vehicle detection methods.

d) Edge: As an important source of contour information, edge has been used widely in vehicle detection. Due to its low computational complexity, edge detection can be performed in a real-time manner. Traditional edge-based vehicle detection methods utilize operators, such as Sobel, Canny, or Prewitt operator to generate horizontal and vertical edge map. Edge is often combined with other features for vehicle detection. In a state-of-art vehicle detection approach, multiscale edge fusion [1] was used to locate target vehicles. Edge often plays the role of providing contour information, while other features provide contextual information to extract vehicle candidates

Extraction of low-level features is fast and convenient, but the main drawback is that one feature cannot efficiently represent all useful information. To solve this problem, one solution is to utilize several features to detect vehicle parts, such as vehicle number plates [121] and vehicle lights [30-35]. A ROI (Region of Interest) is generated based on features such as color, edge, and blob detectors. Based on the visual parts, vehicle candidates can be located successfully. Another solution is to fuse features to extract the whole vehicle(s) in video images. With a combination of two or more than two features, contextual and contour information of vehicles can be extracted in a more effective manner. A brief summary about feature fusion in recent studies can be seen from Table 3, Section 4.

Local Feature Descriptors

In recent studies, there has been a transition from simple low-level features to robust local feature descriptors. Designed for a specific application purpose, feature descriptors allow a quick and efficient search of objects in images. Ideally, descriptors should be able to deal with various objects and robust to varying background, but also be invariant to geometric and photometric transformation [45]. A number of appearance features have been proposed in literatures, among which two features descriptors, the Histograms of Gradients (HOG) and Harr-like features, show increasing prevalence in modern vehicle detection.

a) HOG: Histogram of Gradients (HOG) is a feature descriptor designed for object recognition. By capturing edge of gradient structure that is very characteristic of local shape, HOG was first tested in pedestrian detection [46], and then expanded to the field of moving vehicle detection. In [3], a combination of two HOG vectors was constructed to extract vehicle features. In [89], Pyramid Histograms of Oriented

Gradients (PHOG) features were extracted from traffic images as basic features. In [6], three different configurations involving horizontal (H-HOG), vertical (V-HOG) and concentric rectangular (CR-HOG) descriptors were proposed to perform in a more cost-effective manner than the original HOG. In [90], symmetry HOG vectors were developed for vehicle verification.

b) Haar-like Features: Haar-like features [100] was first proposed by Viola and Jones to detect human faces. Common Haar features include edge, line, and center-surround features. Being simple and easy to compute, it has been used in many vehicle detection approaches for feature representation. In [92], Harr-like feature extraction method was used to represent a vehicle's edges and structures. In [102], a 2D triangle filter was proposed based on Haar-like features to detect vehicles. Sivaraman and Trivedi [93] provided a general learning frame work using Haar-like features. The computation of Haar-like features is fast, however, the dimension of this feature vector generated from images are high [104]. An operation of dimension reduction was then applied to decrease the hardware storage.

c) Other Feature Descriptors: Despite HOG and Haar-like features, some other appearance features also show remarkable effectiveness in collecting contextual information at a regional level. In [9], Gabor features [96] were used to extract taillights. In [37], Gabor features were used to detect vehicles based on rear view. Speed-up Robust Features (SURF) [60] were used to extract the wheel on the back half of the vehicle [47]. In [117], Scale-Invariant Feature Transform (SIFT) features [59] were used to extract interest points in an image, which helps to find the bounding box of a vehicle.

2.2 Hypothesis Verification (HV)

After generating possible candidates from image sequences, the next step is to verify the correctness of hypothesis. Hypothesis Verification (HV) using machine learning method is treated as a two-class pattern classification problem: vehicle versus non-vehicle [92]. Positive images (vehicles class) and negative images (non-vehicle class) are first collected from various sources, then trained with classifiers. In all training samples, each image is represented by one or several feature vectors. Classifiers learn the characteristics of vehicle appearance in a statistical way and draw a decision boundary between the vehicle and non-vehicle class. In order to achieve an optimum appearance-based classification performance, huge within-class variability should be extracted.

SVM (Support Vector Machine), Adaboost and Neural Networks are three representative types of classifiers in vehicle detection. SVM [101] is a discriminative classifier that construct a hyperplane and learn the decision boundary between two classes. Adaboost [73], on the other hand, is a generative weak classifier that improves the performance of a simple classifier by combining local feature descriptors [118]. Neural Networks (NN) [105] have been popular in the past decade, and can learn highly nonlinear decision boundaries [37]. However, Neural Networks suffer from the computation of parameter tuning, therefore being time-consuming. With the development of deep learning technologies, Convolutional Neural Networks (CNN) have been successfully used in vison-based vehicle detection. Fast R-CNN [116] were used for vehicle detection, where a region proposal network (RPN) significantly reduces the proposal cost. In [115], a shallow fully convolutional network called fast vehicle proposal network (FVPN) was proposed to localize all vehicle-like objects in real-time.

Recently, some specific feature-classifier pairs have been widely used in vehicle detection under various conditions, as shown in Table 2. The combinations of HOG features and SVM classifiers [101], and Haar-like features together with Adaboost classifiers, are the most frequently used pairs. Based on existing algorithms, comparative studies have been carried out between features, classifiers and the feature-classifier combinations. HOG and Haar-like features were compared in [120] and utilized to construct a cascade of boosted classifiers for rear-view vehicle detection. SVM and NNs were compared in [37] as HV approaches in both simple and complex scenes. The HOG-SVM and Haar-Adaboost combinations were studied in [97] as an active learning framework.

Table 2. Selected works on feature-classifier combination

Features	Classifiers	Field of View
Gabor	Back propagation neural network [9]	Rear view
	SVM [37]	Rear view
Haar-like	Artificial neural network [76]	Side view
	Adaboost [92, 97]	Rear view
HoG	Adaboost [3]	Rear view
	SVM [90, 97]	Rear view
PHOG - PCA	GA – SVM [89]	Front/Rear view

We see from table 2 that nearly all features depict pixels in terms of orientation information. Gabor features provide scale and orientation information, HoG features calculate gradient magnitude and orientation to construct the histogram, Haar-like features utilize rectangle filters to extract orientation information. At the same time, we observe that most combinations detect and classify vehicles at rear view, only a small portion of detection is from side view. Symmetry can be very useful in front/rear view, and edge features have been utilized in many studies to extract symmetric characteristics of vehicle appearances. Both HOG-SVM and Harr-Adaboost combinations perform well in rear-view images. Being sensitive to edge and symmetric structures, Haar-like features, combined with generative Adaboost classifiers, can perform a rapid detection performance. Different from the Haar-Adaboost combinations, the HOG features focus more on extracting orientations of edges. Therefore, the field of view can be extended from traditional front/rear view to multi-view vehicle detection. In [3], four orientations (front, left, right and far) were selected using HOG features. HOG features were selected and trained to recognize different orientations of vehicles [122].

3 Vehicle Detection- Motion-based Methods

Vehicles on the road are typically in motion, introducing effects of ego and relative motion [48]. Without any prior knowledge, the methods extract moving vehicles based on motion that differentiate from the background [22]. The algorithms are often based on image sequences, while feature-based methods perform either in static images or sequences. Broadly speaking, motion-based vehicle detection can be divided into two categories :1) non-parametric methods and 2) parametric methods.

3.1 Non-parametric Methods

Non-parametric models can be seen as the simplest motion detection method. Without involving any parameters, these methods separate foreground and background in a pixel-by-pixel manner. Frame differencing is a widely-used method in moving vehicle detection, see [57, 58] for earlier works. Traditional two-frame-difference method [44] observes the difference of two successive image frames. The difference image map is obtained by subtracting the intensity of previous frame I_{n-1} from current frame I_n. Thresholding is then chosen to separate image background and foreground, where pixels larger than the threshold value are considered as foreground area (vehicle candidates). The method can generate differencing map in a real-time manner, but is susceptible to illumination changes. The main drawbacks of Frame Differencing are the holes in the segmented objects when the objects move slowly and the ghost behind the segmented object [53]. To detect slow-moving vehicles, a solution was given by in [119], where frame I_n and I_{n+5} were selected to generate binary difference map instead of two consecutive frames. However, when vehicles move fast in video frames, contour information generated by two-frame images overlap. Therefore, a three-frame difference method was proposed in [51]. Two difference image maps were obtained through three video frames. The three-frame difference method was utilised in [44, 50]. Morphorlogical operations of “difference”, “dilate”, “and” [44] and “xor” were then used to fill in the holes and connect the discontinuous edges between two difference images.

Conidering the diversity of vehicle shapes, sizes and colors, non-paramtric models alone may have some limitations in practical cases. Therefore, frame differencing often serves as the first step in vehicle detection. In [49], background subtraction was performed based on binary image generated by frame differencing to detect moving pixels. Frame Differencing was used together with a special-designed feature descriptor to recognize part of a vehicle [119], and with the Gaussian Mixture Model [103] to get a better foreground image in crowded traffic scenes.

3.2 Parametric Methods

In this section, parametric methods are categorized as background modelling, optical flow and other methods.

Background Modelling

This approach aims to build a background model within a video stream. It is assumed that background is stationary and any object that has significant motion is considered part of the foreground [65]. According to [22], background modelling should deal with three problems: 1) What is the model and how does it behave? 2) How is the model initialized? 3)How is the model up-dated over time? The general background modeling algorithms follow the procedure of background initialization, foreground detection and background maintenance.

Gaussian mixture model [54] was introduced by Stauffer and Grimson in 1999. Being one of the most popular background models for moving objects detection, this method assumes all the data points are generated from a mixture of finite Gaussian distributions with unknown parameters. The GMM approach models each pixel using multiple, adaptive Gaussians and uses an on-line approximation to update the model. The method requires two paramenters, the learning rate (α) and threshold (T). In the model matching procedure, GMM requires three Gaussian posibility operations and three comparison operations. In the model updating procedure, GMM requires one Gaussian possibility operation, four subtraction operations and eight multiplication operations [64].

With regard to Gaussian mixture model, some improved methods have been proposed to handle different situations and make this classic approach more efficient. An improved adaptive GMM backgroud subtraction scheme was developed in [68]. This pixel-level approach can automatically select the required number of components and update parameters constantly, thus reducing processing time. By extending traditional pixel-based mixture modelling approaches over neighborhood regions, the generalized framework called the Region-based Mixture of Gaussians was proposed in [11]. The model equations were derived from expectation maximization (EM) theory, and stochastic approximation was used for online update. In [72], the expectation-maximization (EM) algorithm was fused with the Gaussian mixture model for improving the segmentation quality of moving vehicles.

Codebook [61, 62] is another typical background subtraction method. Each pixel is represented by a codebook. Sample background values at each pixel are quantized into codebooks which represent a compressed form of background model for a long image sequence. Five key parameters are involved in this model, four thresholds and one learning rate [23]. Codebook of relevant light feature was used in [69] to add robustness of vehicle light tracking algorithms, showing a near-100% detection rate for vehicle signals.

Optical Flow

Being a typical motion-based method, optical flow has been utilized to detect vehicles for a long time. See [75] for a comprehensive survey on this issue. In [74], a moving vehicle detection algorithm was proposed. Pyramidal optical flow estimation and a morphological transformation operator were used to extract moving vehicle targets. In [77], a refined image process algorithm was utilized to extract features of the vehicle front. The optical flow was then applied herein to implement the vehicle tracking process. In [78], optical flow estimation, distance factor and an accurate feature template were used to track on-road vehicles in low resolution video sequences.

Other Methods

Despite optical flow, there are some other motion-based models. Considering the motion property of dynamic textures in image background is quite different from moving vehicles, motion histogram was used in [53] to segment vehicles from dynamic background. In [94], a vehicle motion model was built according to the scene characteristics. Parameters include average road width, distance to target, standard deviation of target distance, etc. Experiments were implemented in both daytime and nighttime, showing an 86.6% accuracy.

Motion-based models not only play a significant part in detecting vehicles, but also help to reduce the impact of dynamic backgrounds in practical video images, such as swaying trees and flag fluttering [64]. These objects often exhibit certain stationarity properties in time [83], and sometimes it changes from quasi-periodic to irregular motion [23]. As the most common dynamic textures, swaying trees along the roadside are often captured by video cameras and are discussed in some studies. Motion histogram was used in [53] to select a waving trees' region as dynamic ground. In [99], correlation between neighboring image blocks was used to solve swaying tree problems in video images.

Figure 1. Swaying trees in urban driving environments [114].

In a word, appearance-based methods are easy and fast, but the main drawback is high dependence on prior knowledge of vehicles, such as features and templates. Motion-based methods might be time consuming, but are less affected by dynamic background and illuminations. Therefore, we need specific solutions to solve all kinds of on-road vehicle detection problems, at the same time achieve various traffic surveillance objects, as discussed in section 4.

4 Traffic Surveillance Objectives

Recently in the field of ITS, increasing emphasis has been given to issues such as improving safe conditions and optimizing the exploitation of transport network. The endeavors in solving these problems have triggered the interest towards the field of automatic vehicle driving system, where several driver tasks have been proposed [111]. These tasks include, but not limited to, traffic flow estimation, traffic violation detection, vehicle type recognition, incident detection, vehicle counting and vehicle speed measurement.

4.1 Vehicle Counting

Vehicle counting is one key technique in evaluating traffic status, thus conducting traffic flow estimation. The video-based vehicle counting primarily depends on the performances of vehicle detection [108]. In static images, vehicle detection in parking areas have been studied.

Parking area is a place where vehicles are usually densely located. Cameras are mounted along the road side, and the angle of view is different from that on urban roads, see Figure 2. In [9], an effective method to detect vehicles in parking areas was presented. Vehicle taillight information was employed to generate candidates, and a back propagation neural network (BPNN) classifier was used to verify detected vehicle candidates. 53 vehicles can be successfully detected out of 59 vehicles in test images. However, this method operated well based on rear view at daytime, and may be unsuitable in low illumination conditions because vehicle taillight detection is affected easily due to non-uniform illumination. In [7], vehicle detection was carried out in parking lots based on normalized color and edge map. Of all 198 vehicles on cloudy days, 186 vehicles can be successfully detected. Meanwhile, 104 vehicles can be successfully detected out of 109 vehicles on rainy days. Vehicle detection in air craft parking areas was discussed in [56] using multiple cameras. Based on vehicle counting results, volume of flow along a street can be derived, and vehicle speed computed.

Figure 2. Vehicles in parking areas [7].

4.2 Detection of Traffic Incidents

Road traffic safety is a major concern over the past decades. Being an efficient approach to further reduce and avoid traffic accidents, detection of traffic incidents is an important task for video traffic surveillances. In dynamic scenes, many methods have been proposed to address this issue, and mainly discussed driving scenarios include overtaking, illegal turns at intersections and speeding.

Due to the installation location, height and orientation of video cameras, there are different angles of views for vehicles, such as front view, rear view, side view, see Figure 3. Based on different fields of view (FOV), vehicles on road can be categorized as on coming vehicles, preceding vehicles, cross traffic vehicles, etc.

Figure 3. Vehicles in different views [114].

In general cases, vehicles in traffic scenes are detected based on front or rear view [89]. During daytime, rectangular shape can be viewed and interpreted to the utmost extent, and appearance-based features can be utilized in a simple and quick matter, such as vertical/horizontal edges, symmetry, shadow. In nighttime vision, vehicle rear lights serve as an important cue for vehicle detection.

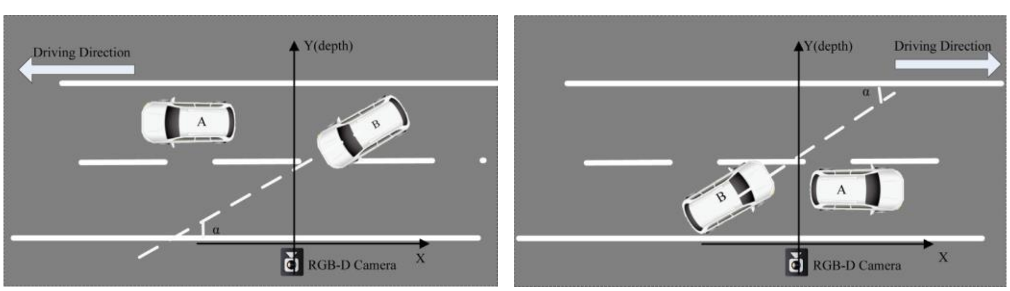
However, vehicles may not be fully visible all the time. When approaching an urban intersection or changing lanes, vehicles may exhibit various orientations and be seen as side views in video images. The side view could be more challenging, because only part of vehicles can be seen in images, and common vehicle detection methods may not be effective in these conditions. Accordingly, vehicle detection based on side view was studied in [47, 64, 84, 88] using different approaches, and many of them focus on overtaking detection and vehicles at intersections.

Vehicle Overtaking

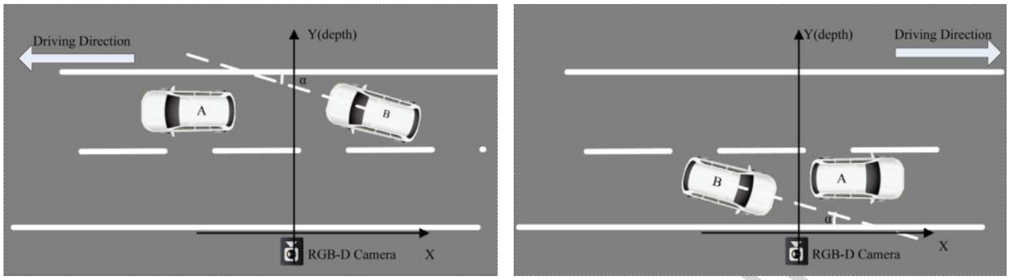
In vehicle overtaking, blind spot of drivers will occur and increase the possibilities of traffic accidents. In [71], data fusion was used for overtaking detection. Fusion was done by information from the radar, and computer vision based on optical flow. Daylight and nightlight conditions were both tested based on rear view, where all the overtaking scenarios were detected. In [70], vehicle overtaking was detected using a method that integrated dynamic scene modeling, hypothesis testing and information fusion. Rear view was chosen and the algorithm showed its robustness in correctly detecting all three overtaking events.

RGB-D camera provides another solution for vehicle overtaking detection. Lost vehicle visual information can be recovered using depth information. Based on the observation that the gray in depth images changes with depth value, posture change of vehicles can be recognized by depth data of RGB-D cameras [98] to detect vehicle overtaking [44]. However, traffic surveillance cameras are 2D in most real-world cases, thus not providing pixel depth information.

In order to address this issue of blind-spot area caused by changing lanes, several blind-spot detection systems have been proposed. A vehicle detection system integrating appearance-based features and edge-based features was proposed in [47], where the camera was mounted on the inside of the right-side window to capture side view. Of all vehicles in test images, approximately 82.1% vehicles can be detected successfully under varying backgrounds (bush, fence, further vehicle and structure). A vision-based blind spot detection system was also presented in [109], using a combination of edge features and support vector machine learning.



(a) (b)



(c) (d)

Figure 4. Illustration of different overtaking scenarios [44]. (a) Left overtaking driving from right to left; (b) Left overtaking driving from left to right;(c) Right overtaking driving form right to left; (d) Left overtaking driving from left to right.

Vehicle Occlusion Handling at Intersections

The recognition and prediction of intersection situations and an accompanying threat assessment are indispensable skill of driving assistance systems [52]. As a special driving scenario in urban environments, vehicles at intersections may suffer from problems of partial occlusions, particularly upon entry and exit from the camera's field of view [84]. When this happens, vehicles sometimes can only be partly seen in image frames. There are many types of occlusion in vehicle detection, and can be categorized in two groups: 1) occlusion among vehicles and 2) occlusion between one vehicle and multiple non-vehicle objects.

Figure 5. Vehicles at intersections [52].

To solve these problems, several solutions have been proposed in literatures. In traditional 2D video images, occlusion can be handled by modelling the vehicle appearance [42]. In [20], an RGB color model with an associated probability mask was defined as an occlusion resolution. Vans with partial occlusion were tracked in this model at intersections. However, the model does not support occlusion handling in variant illumination conditions. A part-based detection approach was used in [88]. Using active learning, vehicle parts were independently detected in a given frame at intersections. In [84], a single detector for front parts and another for rear parts were designed for vehicles facing different orientations. Vehicles at intersections were detected using a self-collected dataset containing 1500 frames. Experimental results show that 91.5% of vehicles can be detected successfully at side view, and 86% of vehicles can be detected successfully with partial occlusion. In [43], an adaptive partial occlusion segmentation method (APPOS) was proposed. Occlusion was detected by finding the abnormal foreground and segmented by the optical flow of contours (OFC) and tested one practical traffic video with urban intersections. In order to address this issue, the LISA-X Intersection dataset was proposed, containing 592 occluded vehicles in grayscale [84]. With partial or full occlusion, vehicle detection at intersections is still a challenging task.

Table 3. A brief summary of vehicle detection approaches based on feature fusion

Reference	Number of features	Features	Angle of view	Application domain
[2]	4	Underneath, vertical edge, symmetry	Rear	Highway scene detection
[5]	4	Sketch, texture, color, flatness	Front	Complex urban traffic conditions (with occlusion)
[7]	3	Color, corner and edge	Up-down	Parking area
[10]	4	Vertical edge, symmetry, HOG and Haar-like features	Rear	Freeway
[19]	2	Shadow, illumination entropy, edge	Rear	Overtaking
[37]	2	Rectangular feature and Gabor filter	Rear	Complex scenes (rain, congested traffic)
[47]	2	Appearance based feature &edge based feature	Side	Blind-spot detection
[102]	2	Haar and triangle features	Rear	Urban scene

5 Environmental Considerations

Due to heavy traffic and complex environmental conditions along different roads, vehicle detection may face various problems. Highways and roads are dynamic environments, with ever-changing backgrounds and illuminations [97]. Accordingly, recognition of vehicles in real-world video sequences is a challenging task, where illumination and weather are two major concerns.

5.1 Illumination

Video cameras provide rich contextual information through measuring ambient light in real world. An image's exposure determines how light or dark an image will appear when it has been captured by the camera [40]. The issue has been studied for many years [86, 87], and is still a challenging problem in vehicle detection. Under urban environments, practical computer vision systems are placed where illumination conditions vary through time [81], in which the changes can be global or local. Global illumination changes refer to different weather, daytime/nighttime conditions in the scene and local illumination changes refer to shadows or highlights of moving objects in the scene.

During daytime, shapes of vehicles are salient thanks to ambient light. Many approaches can be utilized to extract contour and texture information of vehicles in images. However, illumination changes drastically during the transition time of dawn and dusk. Ambient light, as an uncontrolled environmental factor, adds extra difficulty in identifying vehicle appearance in low light conditions.

A simple way to detect vehicles in various light conditions is to use specific detectors for specific cases, e.g. a day time detector for focusing on texture information and a nighttime detector utilizing tail-light information [41]. It is very difficult to develop a universal method for vehicle detection in varying lightning conditions. For this reason, many studies only focus on one or two illumination scenarios.

During the transition time of dawn and dusk, contours and texture information may be present, but vary with saliency and contrast. Preliminary experiments on vehicle detection were conducted in [37], where blob filter was utilized to find rear light candidates. The false positive rate of the break light detection is beneath 4% for the image sequence during dusk, showing its robustness.

Figure 6. Example image taken during dusk (left) and at night (right) [33].

Low light condition was also mentioned in [41]. Four categories of lighting conditions (daylight, low light, night and saturation) were identified using a histogram-based clustering algorithm. Classifiers trained with AdaBoost were used for low light categories. Experiments showed a considerable improvement using the context-adaptive scheme.

At daytime or good weather conditions, various techniques can be used to detect vehicles, and were systematically reviewed in [27]. However, when it comes to nighttime or harsh weather conditions, vehicles are hard to identify due to bad illumination condition. At the same time, many features (edge, corner, shadow etc.) do not work, making vehicle detection more challenging. The only salient visual features are headlights, rear lights and their beams [25]. Therefore, vehicle detection in nighttime utilized local features of vehicle lights as a cue to find candidates. Based on the Nakagami-m distribution, brake lights were modelled and then detected in a part-based manner [38]. In [41], night condition was classified using a clustering algorithm. Then, a taillight detector was used for the nighttime vehicle detection. In [35], brake lights at night were detected by analyzing the signal in both spatial and frequency domains. Rainy images at nighttime were tested as a special case, and 71% vehicles can be detected successfully out of all vehicles.

Vehicle detection in tunnels were categorized as special lighting conditions [2]. Due to overexposure of camera, vertical edges may blur and even disappear in images. Of all 2175 vehicles contained in tunnel images, 1577 vehicles can be detected successfully detected. The detection rate is lower than the detection rate in all scenarios. Another case was discussed in [56], where vehicles were detected in tunnels using stereo vision technologies.

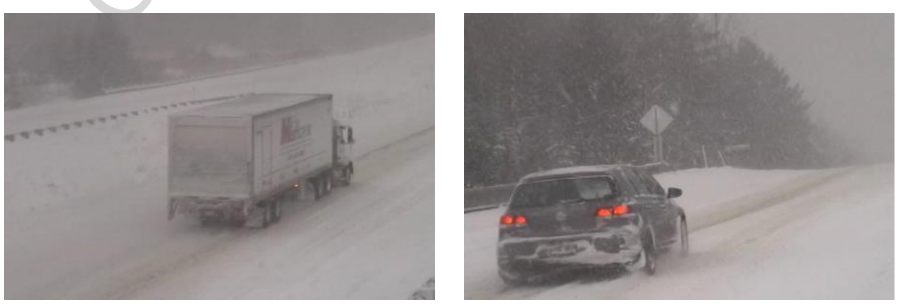
Figure 7. Vehicles in Tunnels [2].

5.2 Weather

In practical cases, there are many environmental factors in outdoor videos that control the image background. On-road driving may face various weather scenarios, e.g. rain, fog, typhoon and snow. In harsh weather conditions, vehicles captured by traffic surveillance cameras exhibit different levels of vagueness, such as darkness, blurring and partial occlusion. At the same time, rain drops, snowflakes that appear in traffic scenes add difficulty in extracting vehicles targets.

A rather simple scene in bad-weather condition is vehicle detection on highways. Based on rear view, experiments were conducted in [37] on rainy days. In [104], vehicles were detected using Haar-like rectangular features and Non-negative Matrix Factorization. Due to the complexity of bad weather, false detection occurs and some vehicles cannot be detected successfully. With the development of computer vision technologies, more efforts have been made in more complicated conditions, such as cloudy, foggy, snowy days. Table 4 shows a brief summary of vehicle detection in different weather conditions. Till now, extreme weather conditions are seldom tested in vehicle detection. On one hand, few driving scenes in ill-weathered conditions are provided in published datasets. On the other hand, vehicle detection approaches that applied to special scenarios have limited applications. In [11], vehicle detection under the blizzard situation was preliminary tested in using region-based Gaussian Mixture Model, with no specific accuracy rate.

In order to test the robustness and applicability of proposed algorithms, many studies have conducted experiments under different weather conditions using either self-collected video sequences or publicly available datasets. Capture video data can be time-consuming, using publicly datasets can be a convenient choice. Several datasets have been proposed, and not much of them contain video sequences under non-perfect weather conditions. In ChangeDetection(CDNet 2014) [12] dataset, the category 'bad weather' contains video sequences of blizzard, snow fall and wet snow, and can be a direct source for training and testing of vehicle detection algorithms. Karlsruhe Institute of Technology (KIT) provided traffic sequences that contain heavy fog and heavy snowfall [123].



(a) (b)

(c) (d)

Figure 8. Vehicle-related scenes in publicly datasets [12] and self-collected images [91]. (a) Vehicle in blizzard; (b) Vehicle in snow fall; (c) Vehicle in wet snow; (d) Vehicles in the rain.

Table 4. Selected works on vehicle detection in different weather conditions

Reference	Methodology	Weather conditions	Accuracy
[7]	Feature fusion (color and edge)	Cloudy, rainy	94.6 % at rainy image, 93.1 % at cloudy image
[1]	Edge fusion based on difference of Gaussian	Cloudy, rainy, foggy, snowy	83.7 % at cloudy image, 74.6 % at rainy image, 70.3 % at foggy image, 72.2 % at snowy image
[91]	Associative Mechanism Model	Rainy, foggy	80.2 % (overall)
[37]	Gabor features	Rainy	Nil
[28]	Feature fusion (shadow and horizontal edge)	Cloudy, rainy, misty	83.3% at dusky image, 95.8% at rainy image, 97.7% at misty image, 96.4% at rainy image
[35]	Feature (taillights)	Rainy	71%

6 Conclusions and Insights

In this study, we have presented a comprehensive review of vehicle detection approaches and its applications in intelligent transportation systems, with a specific focus on varying environments. We first introduced vehicle detection approaches, which can be categorized as appearance-based methods and motion-based methods. Then, we discussed traffic surveillance subjects that can be achieved using vision-based vehicle detection approaches, such as vehicle counting, detection of traffic incidents. There are many environmental factors in outdoor videos that control the image background, and vehicle detection under varying environments are summarized in terms of illumination and weather conditions.

Vehicle detection based on imaging technologies has attracted much attention in past decades, and will remain an active research area in the coming years. From different vehicle detection approaches summarized above, we get the conclusion that each method is suitable to one or two specific conditions, and there is a lack of universal method to automatically detect vehicles under varying environments.

Currently, some studies tested the performance of algorithms using publicly available datasets, such as the Change Detection [12] dataset, GTI database [4], and LISA (Laboratory for intelligent & safe automobiles) dataset [93]. Unlike other fields in computer vison (face detection, object recognition), on-road vehicle detection has fewer publicly available datasets and self-collected video image data is preferred in many studies. It may partly due to the specific designed algorithms, in which a fixed angle of view is required or a particular road is chosen. Sometimes, the camera is even mounted on the vehicle to capture special scenes. With the continuous development of the autonomous vehicles domain, it is certain that more benchmarks will be proposed and used in related studies.

In the future, more sophisticated analysis of vehicle-to-vehicle interaction is required. There is still a heated debate whether on-road vehicle detection should be performed by active sensors or passive sensors. To solve this problem, sensor fusion could be an optimal solution. By means of collecting vehicle information from different sources, researchers gain a deeper understanding of on-road environment, thus detecting vehicles in a more accurate manner. Vision-based vehicle detection has been fused with different sensors, such as radar [71], lasers canner [113] to achieve various traffic surveillance objectives. In reference to the passive sensors, there is a trend to use aerial imagery for vehicle detection in recent studies [112]. As another kind of vision-based sensor, aerial imagery provides vehicle information in a smaller scale and a different field of view. With aerial images, more applications have been enabled, such as oil and gas pipeline threat detection [36], border surveillance [18].

The promising results of the on-road tests demonstrate that a full implementation of traffic surveillance under varying environments is totally feasible. Obviously, computer vision cannot outperform the sensing ability of human eyes. In very harsh conditions, e.g., foggy days with very low visibility or nighttime with no auxiliary lighting, vision-based vehicle detection may not work very accurately, but still helps the prevention of traffic accidents. The ultimate goal of Intelligent Transportation System, in all, is to achieve the best possible vehicle detection performance, and inform road users and traffic managers of real-time driving status under varying environments.

Acknowledgements

This paper was supported by the UGC-funded programme from the Hong Kong Polytechnic University.

References

1. Mu, K., Hui, F., Zhao, X., & Prehofer, C. (2016). Multiscale edge fusion for vehicle detection based on difference of Gaussian. Optik-International Journal for Light and Electron Optics, 127(11), 4794-4798. http://dx.doi.org/10.1016/j.ijleo.2016.01.017
2. Chan, Y. M., Huang, S. S., Fu, L. C., & Hsiao, P. Y. (2007, September). Vehicle detection under various lighting conditions by incorporating particle filter. In Intelligent Transportation Systems Conference, 2007. ITSC 2007. IEEE (pp. 534-539). IEEE. http://dx.doi.org/10.1109/ITSC.2007.4357745
3. Yan, G., Yu, M., Yu, Y., & Fan, L. (2016). Real-time vehicle detection using histograms of oriented gradients and AdaBoost classification. Optik-International Journal for Light and Electron Optics. http://dx.doi.org/10.1016/j.ijleo.2016.05.092
4. Arróspideh, J. (2016). GTI Vehicle Database . [Online]. Available: https://www.gti.ssr.upm.es/data/Vehicle_database.html
5. Li, Y., & Wang, F. Y. (2015). Vehicle detection based on And–Or Graph and Hybrid Image Templates for complex urban traffic conditions. Transportation Research Part C: Emerging Technologies, 51, 19-28. http://dx.doi.org/10.1016/j.trc.2014.10.009
6. Arróspide, J., Salgado, L., & Camplani, M. (2013). Image-based on-road vehicle detection using cost-effective Histograms of Oriented Gradients. Journal of Visual Communication and Image Representation, 24(7), 1182-1190. http://dx.doi.org/10.1016/j.jvcir.2013.08.001
7. Tsai, L. W., Hsieh, J. W., & Fan, K. C. (2007). Vehicle detection using normalized color and edge map. Image Processing, IEEE Transactions on,16(3), 850-864. http://dx.doi.org/10.1109/TIP.2007.891147
8. Wang, X., Tang, J., Niu, J., & Zhao, X. (2016). Vision-based two-step brake detection method for vehicle collision avoidance. Neurocomputing, 173, 450-461. http://dx.doi.org/10.1016/j.neucom.2015.04.117
9. Ming, Q., & Jo, K. H. (2011, August). Vehicle detection using tail light segmentation. In Strategic Technology (IFOST), 2011 6th International Forum on (Vol. 2, pp. 729-732). IEEE. http://dx.doi.org/10.1109/IFOST.2011.6021126
10. Wang, H., & Cai, Y. (2015). Monocular based road vehicle detection with feature fusion and cascaded Adaboost algorithm. Optik-International Journal for Light and Electron Optics, 126(22), 3329-3334. http://dx.doi.org/10.1016/j.ijleo.2015.08.018

11. Varadarajan, S., Miller, P., & Zhou, H. (2015). Region-based Mixture of Gaussians modelling for foreground detection in dynamic scenes. Pattern Recognition, 48(11), 3488-3503. http://dx.doi.org/10.1016/j.patcog.2015.04.016
12. Wang, Y., Jodoin, P. M., Porikli, F., Konrad, J., Benezeth, Y., & Ishwar, P. (2014). CDnet 2014: an expanded change detection benchmark dataset. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (pp. 387-394). http://dx.doi.org/10.1109/CVPRW.2014.126
13. Kuehnle, A. (1991). Symmetry-based recognition of vehicle rears. Pattern recognition letters, 12(4), 249-258. http://dx.doi.org/10.1016/0167-8655(91)90039-O
14. Zielke, T., Brauckmann, M., & Vonseelen, W. (1993). Intensity and edge-based symmetry detection with an application to car-following. CVGIP: Image Understanding, 58(2), 177-190. http://dx.doi.org/10.1006/ciun.1993.1037
15. Collado, J. M., Hilario, C., De la Escalera, A., & Armingol, J. M. (2004, June). Model based vehicle detection for intelligent vehicles. In Intelligent Vehicles Symposium, 2004 IEEE (pp. 572-577). IEEE. http://dx.doi.org/10.1109/IVS.2004.1336447
16. Liu, W., Wen, X., Duan, B., Yuan, H., & Wang, N. (2007, June). Rear vehicle detection and tracking for lane change assist. In 2007 IEEE Intelligent Vehicles Symposium (pp. 252-257). IEEE. http://dx.doi.org/10.1109/IVS.2007.4290123
17. Teoh, S. S., & Bräunl, T. (2012). Symmetry-based monocular vehicle detection system. Machine Vision and Applications, 23(5), 831-842. http://dx.doi.org/10.1007/s00138-011-0355-7
18. Fytsilis, A. L., Prokos, A., Koutroumbas, K. D., Michail, D., & Kontoes, C. C. (2016). A methodology for near real-time change detection between Unmanned Aerial Vehicle and wide area satellite images. ISPRS Journal of Photogrammetry and Remote Sensing, 119, 165-186. http://dx.doi.org/10.1016/j.isprsjprs.2016.06.001
19. Chong, Y., Chen, W., Li, Z., Lam, W. H., Zheng, C., & Li, Q. (2013). Integrated real-time vision-based preceding vehicle detection in urban roads. Neurocomputing, 116, 144-149. http://dx.doi.org/10.1016/j.neucom.2011.11.036
20. Senior, A., Hampapur, A., Tian, Y. L., Brown, L., Pankanti, S., & Bolle, R. (2006). Appearance models for occlusion handling. Image and Vision Computing, 24(11), 1233-1243. http://dx.doi.org/10.1016/j.imavis.2005.06.007
21. Lan, J., Li, J., Hu, G., Ran, B., & Wang, L. (2014). Vehicle speed measurement based on gray constraint optical flow algorithm. Optik-International Journal for Light and Electron Optics, 125(1), 289-295. http://dx.doi.org/10.1016/j.ijleo.2013.06.036

22. Barnich, O., & Van Droogenbroeck, M. (2011). ViBe: A universal background subtraction algorithm for video sequences. IEEE Transactions on Image processing, 20(6), 1709-1724. http://dx.doi.org/10.1109/TIP.2010.2101613
23. Shah, M., Deng, J. D., & Woodford, B. J. (2015). A Self-adaptive CodeBook (SACB) model for real-time background subtraction. Image and Vision Computing, 38, 52-64. http://dx.doi.org/10.1016/j.imavis.2015.02.001
24. Yang, Y., Gao, X., & Yang, G. (2011). Study the method of vehicle license locating based on color segmentation. Procedia Engineering, 15, 1324-1329. http://dx.doi.org/10.1016/j.proeng.2011.08.245
25. Cucchiara, R., Piccardi, M., & Mello, P. (2000). Image analysis and rule-based reasoning for a traffic monitoring system. IEEE Transactions on Intelligent Transportation Systems, 1(2), 119-130. http://dx.doi.org/10.1109/6979.880969
26. O'Malley, R., Jones, E., & Glavin, M. (2010). Rear-lamp vehicle detection and tracking in low-exposure color video for night conditions. IEEE Transactions on Intelligent Transportation Systems, 11(2), 453-462. http://dx.doi.org/10.1109/TITS.2010.2045375
27. Sun, Z., Bebis, G., & Miller, R. (2006). On-road vehicle detection: A review. IEEE transactions on pattern analysis and machine intelligence, 28(5), 694-711. http://dx.doi.org/10.1109/TPAMI.2006.104
28. Shen, X. L., Tseng D. C. (2007). Vision Detection of Lanes and Vehicles for Advanced Safety Vehicles. [Online]. Available: http://etd.lib.nctu.edu.tw/cgi-bin/gs32/ncugsweb.cgi/ccd=tdYkFz/fulltextstdcdr?dbid=qjwHXE%255DMWcIa&dbpathf=/opt/fb32/db/ncu/ncucdrf/&fuid=01&dbna=
29. Thammakaroon, P., & Tangamchit, P. (2009, July). Predictive brake warning at night using taillight characteristic. In 2009 IEEE International Symposium on Industrial Electronics (pp. 217-221). IEEE. http://dx.doi.org/10.1109/ISIE.2009.5218254
30. Skodras, E., Siogkas, G., Dermatas, E., & Fakotakis, N. (2012, April). Rear lights vehicle detection for collision avoidance. In 2012 19th International Conference on Systems, Signals and Image Processing (IWSSIP) (pp. 134-137). IEEE. [Online]. Available: http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=6208089
31. Cabani, I., Toulminet, G., & Bensrhair, A. (2005, June). Color-based detection of vehicle lights. In IEEE Proceedings. Intelligent Vehicles Symposium, 2005. (pp. 278-283). IEEE. http://dx.doi.org/10.1109/IVS.2005.1505115

32. Chen, H. T., Wu, Y. C., & Hsu, C. C. (2016). Daytime Preceding Vehicle Brake Light Detection Using Monocular Vision. IEEE Sensors Journal, 16(1), 120-131. http://dx.doi.org/10.1109/JSEN.2015.2477412
33. Schamm, T., von Carlowitz, C., & Zöllner, J. M. (2010, June). On-road vehicle detection during dusk and at night. In Intelligent Vehicles Symposium (IV), 2010 IEEE (pp. 418-423). IEEE. http://dx.doi.org/10.1109/IVS.2010.5548013
34. O'Malley, R., Glavin, M., & Jones, E. (2008, July). Vehicle detection at night based on tail-light detection. In Proceedings of the 1st International Symposium on Vehicular Computing Systems, Trinity College, Dublin (Vol. 2224). [Online]. Available: https://www.researchgate.net/profile/Martin_Glavin/publication/251423714_Vehicle_Detection_at_Night_Based_on_TailLight_Detection/links/02e7e529edba677199000000.pdf
35. Chen, D. Y., & Peng, Y. J. (2012). Frequency-tuned taillight-based nighttime vehicle braking warning system. IEEE Sensors Journal, 12(11), 3285-3292. http://dx.doi.org/10.1109/JSEN.2012.2212971
36. Gleason, J., Nefian, A. V., Bouyssounousse, X., Fong, T., & Bebis, G. (2011, May). Vehicle detection from aerial imagery. In Robotics and Automation (ICRA), 2011 IEEE International Conference on (pp. 2065-2070). IEEE. http://dx.doi.org/10.1109/ICRA.2011.5979853
37. Sun, Z., Bebis, G., & Miller, R. (2006). Monocular precrash vehicle detection: features and classifiers. IEEE transactions on image processing,15(7), 2019-2034. http://dx.doi.org/10.1109/TIP.2006.877062
38. Chen, D. Y., Lin, Y. H., & Peng, Y. J. (2012). Nighttime brake-light detection by Nakagami imaging. IEEE Transactions on Intelligent Transportation Systems, 13(4), 1627-1637. http://dx.doi.org/10.1109/TITS.2012.2199983
39. Wang, C. C., Huang, S. S., & Fu, L. C. (2005, August). Driver assistance system for lane detection and vehicle recognition with night vision. In 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems (pp. 3530-3535). IEEE. http://dx.doi.org/10.1109/IROS.2005.1545482
40. Martínez, J., Santos, M., & López, V. (2014). Photograph's Exposure Control by Fuzzy Logic. In Practical Applications of Intelligent Systems (pp. 293-303). Springer Berlin Heidelberg. http://dx.doi.org/10.1007/978-3-642-54927-4_28
41. Acunzo, D., Zhu, Y., Xie, B., & Baratoff, G. (2007, September). Context-adaptive approach for vehicle detection under varying lighting conditions. In 2007 IEEE Intelligent Transportation Systems Conference (pp. 654-660). IEEE. http://dx.doi.org/10.1109/ITSC.2007.4357724

42. Tian, B., Tang, M., & Wang, F. Y. (2015). Vehicle detection grammars with partial occlusion handling for traffic surveillance. Transportation Research Part C: Emerging Technologies, 56, 80-93. http://dx.doi.org/10.1016/j.trc.2015.02.020
43. Zhao, N., Xia, Y., Xu, C., Shi, X., & Liu, Y. (2016). APPOS: An adaptive partial occlusion segmentation method for multiple vehicles tracking. Journal of Visual Communication and Image Representation, 37, 25-31. http://dx.doi.org/10.1016/j.jvcir.2015.04.011
44. Xia, Y., Wang, C., Shi, X., & Zhang, L. (2015). Vehicles overtaking detection using RGB-D data. Signal Processing, 112, 98-109. http://dx.doi.org/10.1016/j.sigpro.2014.07.025
45. Li, J., & Allinson, N. M. (2008). A comprehensive review of current local features for computer vision. Neurocomputing, 71(10), 1771-1787. http://dx.doi.org/10.1016/j.neucom.2007.11.032
46. Dalal, Navneet, and Bill Triggs. "Histograms of oriented gradients for human detection." 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05). Vol. 1. IEEE, 2005. http://dx.doi.org/10.1109/CVPR.2005.177
47. Lin, B. F., Chan, Y. M., Fu, L. C., Hsiao, P. Y., Chuang, L. A., Huang, S. S., & Lo, M. F. (2012). Integrating appearance and edge features for sedan vehicle detection in the blind-spot area. IEEE Transactions on Intelligent Transportation Systems, 13(2), 737-747. http://dx.doi.org/10.1109/TITS.2011.2182649
48. Sivaraman, S., & Trivedi, M. M. (2013). Looking at vehicles on the road: A survey of vision-based vehicle detection, tracking, and behavior analysis. IEEE Transactions on Intelligent Transportation Systems, 14(4), 1773-1795. http://dx.doi.org/10.1109/TITS.2013.2266661
49. Celik, T., & Kusetogullari, H. (2010). Solar-powered automated road surveillance system for speed violation detection. IEEE Transactions on Industrial Electronics, 57(9), 3216-3227. http://dx.doi.org/10.1109/TIE.2009.2038395
50. Lan, J., Li, J., Hu, G., Ran, B., & Wang, L. (2014). Vehicle speed measurement based on gray constraint optical flow algorithm. Optik-International Journal for Light and Electron Optics, 125(1), 289-295. http://dx.doi.org/10.1016/j.ijleo.2013.06.036
51. Weng, M., Huang, G., & Da, X. (2010, October). A new interframe difference algorithm for moving target detection. In Image and Signal Processing (CISP), 2010 3rd International Congress on (Vol. 1, pp. 285-289). IEEE. http://dx.doi.org/10.1109/CISP.2010.5648259
52. Kafer, E., Hermes, C., Wohler, C., Kummert, F., & Ritter, H. (2010, August). Recognition and prediction of situations in urban traffic scenarios. In Pattern Recognition (ICPR), 2010 20th International Conference on (pp. 4234-4237). IEEE. http://dx.doi.org/10.1109/ICPR.2010.1029

53. Zhang, W., Wu, Q. J., & bing Yin, H. (2010). Moving vehicles detection based on adaptive motion histogram. Digital Signal Processing, 20(3), 793-805. http://dx.doi.org/10.1016/j.dsp.2009.10.006
54. Stauffer, C., & Grimson, W. E. L. (1999). Adaptive background mixture models for real-time tracking. In Computer Vision and Pattern Recognition, 1999. IEEE Computer Society Conference on. (Vol. 2). IEEE. http://dx.doi.org/10.1109/CVPR.1999.784637
55. Spagnolo, P., Leo, M., & Distante, A. (2006). Moving object segmentation by background subtraction and temporal analysis. Image and Vision Computing,24(5), 411-423. http://dx.doi.org/10.1016/j.imavis.2006.01.001
56. Semertzidis, T., Dimitropoulos, K., Koutsia, A., & Grammalidis, N. (2010). Video sensor network for real-time traffic monitoring and surveillance. IET intelligent transport systems, 4(2), 103-112. http://dx.doi.org/10.1049/iet-its.2008.0092
57. Kim, J. B., & Kim, H. J. (2003). Efficient region-based motion segmentation for a video monitoring system. Pattern Recognition Letters, 24(1), 113-128. http://dx.doi.org/10.1016/S0167-8655(02)00194-0
58. Li, X., Liu, Z. Q., & Leung, K. M. (2002). Detection of vehicles from traffic scenes using fuzzy integrals. Pattern Recognition, 35(4), 967-980. http://dx.doi.org/10.1016/S0031-3203(01)00079-6
59. Lowe, D. G. (1999). Object recognition from local scale-invariant features. In Computer vision, 1999. The proceedings of the seventh IEEE international conference on (Vol. 2, pp. 1150-1157). Ieee. http://dx.doi.org/10.1109/ICCV.1999.790410
60. Bay, H., Tuytelaars, T., & Van Gool, L. (2006, May). Surf: Speeded up robust features. In European conference on computer vision (pp. 404-417). Springer Berlin Heidelberg. http://dx.doi.org/10.1007/11744023_32
61. Kim, K., Chalidabhongse, T. H., Harwood, D., & Davis, L. (2004, October). Background modeling and subtraction by codebook construction. In Image Processing, 2004. ICIP'04. 2004 International Conference on (Vol. 5, pp. 3061-3064). IEEE. http://dx.doi.org/10.1109/ICIP.2004.1421759
62. Kim, K., Chalidabhongse, T. H., Harwood, D., & Davis, L. (2005). Real-time foreground–background segmentation using codebook model. Real-time imaging, 11(3), 172-185. http://dx.doi.org/10.1016/j.rti.2004.12.004
63. Elgammal, A., Harwood, D., & Davis, L. (2000, June). Non-parametric model for background subtraction. In European conference on computer vision (pp. 751-767). Springer Berlin Heidelberg. http://dx.doi.org/10.1007/3-540-45053-X_48

64. Zhang, W., Fang, X., Yang, X., & Wu, Q. J. (2007). Spatiotemporal Gaussian mixture model to detect moving objects in dynamic scenes.Journal of Electronic Imaging, 16(2), 023013-023013. http://dx.doi.org/10.1117/1.2731329
65. Gupte, S., Masoud, O., Martin, R. F., & Papanikolopoulos, N. P. (2002). Detection and classification of vehicles. IEEE Transactions on intelligent transportation systems, 3(1), 37-47. http://dx.doi.org/10.1109/6979.994794
66. Mandellos, N. A., Keramitsoglou, I., & Kiranoudis, C. T. (2011). A background subtraction algorithm for detecting and tracking vehicles. Expert Systems with Applications, 38(3), 1619-1631. http://dx.doi.org/10.1016/j.eswa.2010.07.083
67. Patel, C., Shah, D., & Patel, A. (2013). Automatic number plate recognition system (ANPR): A survey. International Journal of Computer Applications,69(9). http://dx.doi.org/10.5120/11871-7665
68. Zivkovic, Z. (2004, August). Improved adaptive Gaussian mixture model for background subtraction. In Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on (Vol. 2, pp. 28-31). IEEE. http://dx.doi.org/10.1109/ICPR.2004.1333992
69. Almagambetov, A., Casares, M., & Velipasalar, S. (2012, July). Autonomous tracking of vehicle rear lights and detection of brakes and turn signals. In2012 IEEE Symposium on Computational Intelligence for Security and Defence Applications (pp. 1-7). IEEE. http://dx.doi.org/10.1109/CISDA.2012.6291543
70. Zhu, Y., Comaniciu, D., Pellkofer, M., & Koehler, T. (2006). Reliable detection of overtaking vehicles using robust information fusion. IEEE Transactions on Intelligent Transportation Systems, 7(4), 401-414. http://dx.doi.org/10.1109/TITS.2006.883936
71. Garcia, F., Cerri, P., Broggi, A., de la Escalera, A., & Armingol, J. M. (2012, June). Data fusion for overtaking vehicle detection based on radar and optical flow. In Intelligent Vehicles Symposium (IV), 2012 IEEE (pp. 494-499). IEEE. http://dx.doi.org/10.1109/IVS.2012.6232199
72. Xia, Y., Shi, X., Song, G., Geng, Q., & Liu, Y. (2016). Towards improving quality of video-based vehicle counting method for traffic flow estimation.Signal Processing, 120, 672-681. http://dx.doi.org/10.1016/j.sigpro.2014.10.035
73. Freund, Y., & Schapire, R. E. (1995, March). A desicion-theoretic generalization of on-line learning and an application to boosting. In European conference on computational learning theory (pp. 23-37). Springer Berlin Heidelberg. http://dx.doi.org/10.1007/3-540-59119-2_166
74. Zhan, W., & Ji, X. (2011). Algorithm research on moving vehicles detection.Procedia Engineering, 15, 5483-5487. http://dx.doi.org/10.1016/j.proeng.2011.08.1017

75. Fortun, D., Bouthemy, P., & Kervrann, C. (2015). Optical flow modeling and computation: a survey. Computer Vision and Image Understanding, 134, 1-21. http://dx.doi.org/10.1016/j.cviu.2015.02.008
76. Mohamed, A., Issam, A., Mohamed, B., & Abdellatif, B. (2015). Real-time Detection of Vehicles Using the Haar-like Features and Artificial Neuron Networks. Procedia Computer Science, 73, 24-31. http://dx.doi.org/10.1016/j.procs.2015.12.044
77. Kuo, Y. C., Pai, N. S., & Li, Y. F. (2011). Vision-based vehicle detection for a driver assistance system. Computers & Mathematics with Applications,61(8), 2096-2100. http://dx.doi.org/10.1016/j.camwa.2010.08.081
78. Liu, Y., Lu, Y., Shi, Q., & Ding, J. (2013, December). Optical flow based urban road vehicle tracking. In Computational Intelligence and Security (CIS), 2013 9th International Conference on (pp. 391-395). IEEE. http://dx.doi.org/10.1109/CIS.2013.89
79. Prati, A., Mikic, I., Trivedi, M. M., & Cucchiara, R. (2003). Detecting moving shadows: algorithms and evaluation. IEEE transactions on pattern analysis and machine intelligence, 25(7), 918-923. http://dx.doi.org/10.1109/TPAMI.2003.1206520
80. Horprasert, T., Harwood, D., & Davis, L. S. (1999, September). A statistical approach for real-time robust background subtraction and shadow detection. In Ieee iccv (Vol. 99, pp. 1-19). [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.87.1244&rep=rep1&type=pdf
81. López-Rubio, F. J., & López-Rubio, E. (2015). Local color transformation analysis for sudden illumination change detection. Image and Vision Computing, 37, 31-47. http://dx.doi.org/10.1016/j.imavis.2015.03.001
82. Cucchiara, R., Grana, C., Piccardi, M., & Prati, A. (2003). Detecting moving objects, ghosts, and shadows in video streams. IEEE transactions on pattern analysis and machine intelligence, 25(10), 1337-1342. http://dx.doi.org/10.1109/TPAMI.2003.1233909
83. Doretto, G., Chiuso, A., Wu, Y. N., & Soatto, S. (2003). Dynamic textures. International Journal of Computer Vision, 51(2), 91-109. http://dx.doi.org/10.1109/ICCV.2001.937658
84. Sivaraman, S., & Trivedi, M. M. (2013). Vehicle detection by independent parts for urban driver assistance. IEEE transactions on intelligent transportation systems, 14(4), 1597-1608. http://dx.doi.org/10.1109/TITS.2013.2264314
85. Tzomakas, C., & von Seelen, W. (1998). Vehicle detection in traffic scenes using shadows. In IR-INI, INSTITUT FUR NUEROINFORMATIK, RUHR-UNIVERSITAT. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.45.3234&rep=rep1&type=pdf

86. Mikic, I., Cosman, P. C., Kogut, G. T., & Trivedi, M. M. (2000). Moving shadow and object detection in traffic scenes. In Pattern Recognition, 2000. Proceedings. 15th International Conference on (Vol. 1, pp. 321-324). IEEE. http://dx.doi.org/10.1109/ICPR.2000.905341
87. Kilger, M. (1992, November). A shadow handler in a video-based real-time traffic monitoring system. In Applications of Computer Vision, Proceedings, 1992., IEEE Workshop on (pp. 11-18). IEEE. http://dx.doi.org/10.1109/ACV.1992.240332
88. Sivaraman, S., & Trivedi, M. M. (2012, September). Real-time vehicle detection using parts at intersections. In 2012 15th International IEEE Conference on Intelligent Transportation Systems (pp. 1519-1524). IEEE. http://dx.doi.org/10.1109/ITSC.2012.6338886
89. Khairdoost, N., Monadjemi, S. A., & Jamshidi, K. (2013). Front and rear vehicle detection using hypothesis generation and verification. Signal & Image Processing, 4(4), 31. http://dx.doi.org/10.5121/sipij.2013.4403
90. Cheon, M., Lee, W., Yoon, C., & Park, M. (2012). Vision-based vehicle detection system with consideration of the detecting location. IEEE transactions on intelligent transportation systems, 13(3), 1243-1252. http://dx.doi.org/10.1109/TITS.2012.2188630
91. Jia, D., Zhu, H., Zou, S., & Huang, K. (2016). Recognition method based on Green Associative Mechanism for weak contrast vehicle targets. Neurocomputing, 203, 1-11. http://dx.doi.org/10.1016/j.neucom.2016.03.045
92. Wen, X., Shao, L., Fang, W., & Xue, Y. (2015). Efficient feature selection and classification for vehicle detection. IEEE Transactions on Circuits and Systems for Video Technology, 25(3), 508-517. http://dx.doi.org/10.1109/TCSVT.2014.2358031
93. Sivaraman, S., & Trivedi, M. M. (2010). A general active-learning framework for on-road vehicle recognition and tracking. IEEE Transactions on Intelligent Transportation Systems, 11(2), 267-276. http://dx.doi.org/10.1109/TITS.2010.2040177
94. Jazayeri, A., Cai, H., Zheng, J. Y., & Tuceryan, M. (2011). Vehicle detection and tracking in car video based on motion model. IEEE Transactions on Intelligent Transportation Systems, 12(2), 583-595. http://dx.doi.org/10.1109/TITS.2011.2113340
95. Khammari, A., Nashashibi, F., Abramson, Y., & Laurgeau, C. (2005, September). Vehicle detection combining gradient analysis and AdaBoost classification. In Proceedings. 2005 IEEE Intelligent Transportation Systems, 2005. (pp. 66-71). IEEE. http://dx.doi.org/10.1109/ITSC.2005.1520202
96. Tao, D., Li, X., Wu, X., & Maybank, S. J. (2007). General tensor discriminant analysis and gabor features for gait recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 29(10), 1700-1715. http://dx.doi.org/10.1109/TPAMI.2007.1096

97. Sivaraman, S., & Trivedi, M. M. (2014). Active learning for on-road vehicle detection: a comparative study. Machine vision and applications, 25(3), 599-611. http://dx.doi.org/10.1007/s00138-011-0388-y
98. Harville, M., Gordon, G., & Woodfill, J. (2001). Adaptive video background modeling using color and depth. In Image Processing, 2001. Proceedings. 2001 International Conference on (Vol. 3, pp. 90-93). IEEE. http://dx.doi.org/10.1109/ICIP.2001.958058
99. Seki, M., Wada, T., Fujiwara, H., & Sumi, K. (2003, June). Background subtraction based on cooccurrence of image variations. In Computer Vision and Pattern Recognition, 2003. Proceedings. 2003 IEEE Computer Society Conference on (Vol. 2, pp. II-65). IEEE. http://dx.doi.org/10.1109/CVPR.2003.1211453
100. Viola, P., & Jones, M. (2001). Rapid object detection using a boosted cascade of simple features. In Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on (Vol. 1, pp. I-511). IEEE. http://dx.doi.org/10.1109/CVPR.2001.990517
101. Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine learning,20(3), 273-297. http://dx.doi.org/10.1007/BF00994018
102. Haselhoff, A., & Kummert, A. (2009, June). A vehicle detection system based on haar and triangle features. In Intelligent Vehicles Symposium, 2009 IEEE (pp. 261-266). IEEE. http://dx.doi.org/10.1109/IVS.2009.5164288
103. Fu, H., Ma, H., Liu, Y., & Lu, D. (2016). A Vehicle Classification System Based on Hierarchical Multi-SVMs in Crowded Traffic Scenes. Neurocomputing. http://dx.doi.org/10.1016/j.neucom.2015.12.134
104. Wang, H., Yuan, C., & Cai, Y. (2015). Smart road vehicle sensing system based on monocular vision. Optik-International Journal for Light and Electron Optics, 126(4), 386-390. http://dx.doi.org/10.1016/j.ijleo.2014.09.010
105. Bishop, C. M. (1995). Neural networks for pattern recognition. Oxford university press. [Online]. Available: http://www.cs.ukzn.ac.za/~sviriri/Books/Machine-Learning-Pattern-Recognition/book5.pdf
106. Asaidi, H., Aarab, A., & Bellouki, M. (2014). Shadow elimination and vehicles classification approaches in traffic video surveillance context. Journal of Visual Languages & Computing, 25(4), 333-345. http://dx.doi.org/10.1016/j.jvlc.2014.02.001
107. Abolghasemi, V., & Ahmadyfard, A. (2009). An edge-based color-aided method for license plate detection. Image and Vision Computing, 27(8), 1134-1142. http://dx.doi.org/10.1016/j.imavis.2008.10.012

108. Bas, E., Tekalp, A. M., & Salman, F. S. (2007, June). Automatic vehicle counting from video for traffic flow analysis. In 2007 IEEE Intelligent Vehicles Symposium (pp. 392-397). IEEE. http://dx.doi.org/10.1109/IVS.2007.4290146

109. Blanc, N., Steux, B., & Hinz, T. (2007, June). LaRASideCam: A fast and robust vision-based blindspot detection system. In 2007 IEEE Intelligent Vehicles Symposium (pp. 480-485). IEEE. http://dx.doi.org/10.1109/IVS.2007.4290161

110. Directive, E. C. (2010). 40/EU European Parliament and of the Council of 7 July 2010 on the framework for the deployment of Intelligent Transport Systems in the field of road transport and for interfaces with other modes of transport. L207/1, 6. [Online]. Available: http://tn-its.eu/docs/ec/ITS-Directive-100707.pdf

111. Bertozzi, M., Broggi, A., & Fascioli, A. (2000). Vision-based intelligent vehicles: State of the art and perspectives. Robotics and Autonomous systems, 32(1), 1-16. http://dx.doi.org/10.1016/S0921-8890(99)00125-6

112. Razakarivony, S., & Jurie, F. (2016). Vehicle detection in aerial imagery: a small target detection benchmark. Journal of Visual Communication and Image Representation, 34, 187-203. http://dx.doi.org/10.1016/j.jvcir.2015.11.002

113. Kaempchen, N., & Dietmayer, K. (2004, October). Fusion of laserscanner and video for advanced driver assistance systems. In IEEE Int. Conf. on Intelligent Transportation System. [Online]. Available: https://www.researchgate.net/profile/Nico_Kaempchen/publication/237690334_FUSION_OF_LASERSCANNER_AND_VIDEO_FOR_ADVANCED_DRIVER_ASSISTANCE_SYSTEMS/links/564050da08ae8d65c015187d.pdf

114. Hong Kong eTransport. (2016). Retrieved 08 2016, from Transport Department of Hong Kong. [Online]. Available: http://traffic.td.gov.hk/SwitchCenter.do

115. Zhou, Y., Liu, L., Shao, L., & Mellor, M. (2016, October). DAVE: A Unified Framework for Fast Vehicle Detection and Annotation. In European Conference on Computer Vision (pp. 278-293). Springer International Publishing. https://doi.org/10.1007/978-3-319-46475-6_18

116. Fan, Q., Brown, L., & Smith, J. (2016, June). A closer look at Faster R-CNN for vehicle detection. In Intelligent Vehicles Symposium (IV), 2016 IEEE (pp. 124-129). IEEE. https://doi.org/10.1016/j.trit.2016.09.001

117. Zhang, X., Zheng, N., He, Y., & Wang, F. (2011, October). Vehicle detection using an extended

hidden random field model. In Intelligent Transportation Systems (ITSC), 2011 14th International IEEE Conference on (pp. 1555-1559). IEEE. http://dx.doi.org/10.1109/ITSC.2011.6083135

118. Buch, N., Velastin, S. A., & Orwell, J. (2011). A review of computer vision techniques for the analysis of urban traffic. IEEE Transactions on Intelligent Transportation Systems, 12(3), 920-939. https://doi.org/10.1109/TITS.2011.2119372

119. Ji, W., Tang, L., Li, D., Yang, W., & Liao, Q. (2016). Video-based construction vehicles detection and its application in intelligent monitoring system. CAAI Transactions on Intelligence Technology, 1(2), 162-172. https://doi.org/10.1016/j.trit.2016.09.001

120. Negri, P., Clady, X., Hanif, S. M., & Prevost, L. (2008). A cascade of boosted generative and discriminative classifiers for vehicle detection. EURASIP Journal on Advances in Signal Processing, 2008, 136. https://doi.org/10.1155/2008/782432

121. Patel, C., Shah, D., & Patel, A. (2013). Automatic number plate recognition system (anpr): A survey. International Journal of Computer Applications, 69(9). http://dx.doi.org/10.5120/11871-7665

122. Rybski, P. E., Huber, D., Morris, D. D., & Hoffman, R. (2010, June). Visual classification of coarse vehicle orientation using histogram of oriented gradients features. In Intelligent Vehicles Symposium (IV), 2010 IEEE (pp. 921-928). IEEE. https://doi.org/10.1109/IVS.2010.5547996

123. Karlsruhe Institute of Technology (1997). Image Sequence Server. [online]. Available: http://i21www.ira.uka.de/image_sequences/.

Highlights

- We present an exhaustive review on vision-based vehicle detection
- We categorize methods based on vehicle appearance and vehicle motion
- We discuss various traffic surveillance objectives
- We summarize solutions under varying illumination and weather conditions