Proceedings of the 2nd World Congress on Civil, Structural, and Environmental Engineering (CSEE'17)
Barcelona, Spain – April 2 – 4, 2017
Paper No. ICTE 110
ISSN: 2371-5294
DOI: 10.11159/icte17.110

Vehicle Detection Using Imaging Technologies and its Applications under Varying Environments: A Review

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Abstract **–** Robust and efficient vehicle detection from images 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 to detect vehicles, such as feature-based method and model-based methods. In addition, special illumination, weather and driving scenarios are discussed in terms of methodology and quantitative evaluation. In the future, works should be focused on robust vehicle detection approaches for various on-road conditions.

Keywords**:** Vehicle Detection, Computer Vision, 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' used of transport networks [1], 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 [2] 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. In recent years, there is even a trend to fuse data from different sources [3] to detect vehicles.

Video cameras have been deployed for traffic surveillance for a long time, because they provide a rich contextual information from human visualization and understanding, With the increasing numbers 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 [4].

Many vehicle detection methods have been reported in the literature [5, 6, 7]. Most of them focus on algorithms and technologies used to detect vehicles, while the application domain is seldom summarized. Therefore, the objectives of this review article are: 1) to summarize state-of-the-art vehicle detection approaches in varying environments by using images from video cameras; 2) to compare and evaluate performances of aforementioned approaches for different vehicle detection purposes under different environments.

2. Vehicle Detection Approaches

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 [8]. With the deployment of video cameras, vehicle detection can be categorized as feature-based methods and model-based methods.

2.1. Feature-based Methods

Appearance of vehicles vary in size, shape and color. Feature-based methods employ prior knowledge to segment foreground (contains the objects of interest) and the background (its complementary set) [9]. Due to the rectangular shape of vehicles, various features have been used as important cues for vehicle detection, such as symmetry, color, edge (horizontal/vertical), shadow, etc. Each feature has its own advantages and weakness.

Table 1: A brief summary of local features.

Feature	Descriptions
Color	• Provides rich information in video images • Color of an object depend on illumination, reflectance of the object and sensor parameters, thus may fail due to varying lighting conditions
Shadow	• One kind of local illumination change • May be unidentifiable in bad weather/illumination conditions
Edge	• Important sources of contour information • Low computational complexity • Often combined with other features for vehicle detection
Symmetry	• Effective at the front/rear view • A seldom-used feature in state-of-the-art vehicle detection methods

Feature-based methods are fast and convenient, but the main drawback of feature information is that one feature cannot efficiently represent all useful information. Therefore, most researches choose to use feature fusion in vehicle detection algorithms. With a combination of two or more than two features, contextual and contour information of vehicles can be extracted more effectively from images. In recent years, there has been transition from combined features to robust feature descriptors for moving vehicle detection. Designed for a specific application, these descriptors show remarkable performance in collecting contextual information at a regional level. Gabor, SURF and SIFT feature descriptors are used in early works, whereas two appearance features, HOG and Haar-like features, are frequently used for vehicle detection. At the same time, feature classifier pairs, called as an active learning framework in [10], has been widely used in vehicle detection under various conditions. The combination of HOG feature and SVM classifier, and Haar-like features together with Adaboost classifier, have achieved impressive results in vehicle detection and classification [11].

2.2. Model-based Methods

For real-time moving vehicle detection, background modelling is a common and effective method, which focuses on detecting moving vehicles from background without any prior knowledge. The method is often based on image sequences, while feature-based methods perform either in static images or sequences.

Being one on the most popular parametric models for moving objects detection, Mixture of Gaussians (MoG) is a probabilistic model that assumes all the data points are generated from a mixture of a finite Gaussian distributions with unknown parameters. Two parameters are involved, the learning rate (α) and threshold (T). Some methods have been proposed to handle different situations and improve the segmentation quality of moving vehicles, e.g., the split Gaussian Models [12] the Region-based Mixture of Gaussians (RMoG) [13].

Motion-based models also play a significant part in detecting vehicles. Optical flow, a typical pattern recognition tool, has been used to extract moving vehicle targets [14] and track on-road vehicles in video sequences [15].

3. Traffic Surveillance Objectives under Varying Environments

With the help of efficient and accurate vehicle detection techniques, many traffic surveillance objectives can be supported, such as traffic flow estimation, traffic violation detection, incident detection, vehicle counting and vehicle speed measurement.

3.1. Various Illumination Conditions

Video cameras provide rich context information through measuring ambient light in real world, and represent them using pixels in digital images. Practical computer vision systems are placed where illumination conditions vary through time [16] 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 textural 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. Preliminary experiments on vehicle detection at dusk were conducted in [17], where blob filter was utilized to find rear light candidates.

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 most salient visual features are headlights, taillights and their beams [18]. Therefore, vehicle detection at night mainly utilizes local features of vehicle lights [19] as a cue to find candidates.

3.2. Different Weather Conditions

Due to heavy traffic and complex environmental conditions along different roads, vehicle detection may face various problems. At daytime, real-world video sequences vary in different illumination and weather conditions, making real-time vehicle detection a challenging task.

Table 2: Selected works on vehicle detection in different weather conditions.

Reference	Methodology	Weather conditions	Accuracy
[4]	Feature fusion (color and edge)	Cloudy, rainy	94.6 % at rainy image, 93.1 % at cloudy image
[7]	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
[20]	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
[19]	Feature (taillight)	Rainy	71% at rainy image

Till now, extreme weather condition is seldom studied 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 [13], vehicle detection under the blizzard situation was preliminary tested in using region-based Gaussian Mixture Model, with no specific accuracy rate.

4. Conclusion

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. 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. In the future, more sophisticated analysis of vehicle-to-vehicle interaction is required to obtain a deeper understanding of on-road environment, thus detecting vehicles in a more efficient manner.

Acknowledgements

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

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