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 vehicle detection and classification techniques and also discusses about different approaches detecting the vehicles in bad weather conditions. It also discusses about the datasets used for evaluating the proposed techniques in various studies.

Keywords: Intelligent traffic management · Sensors · Traffic surveillance · Image processing · Vehicle detection · Vehicle classification

1 Introduction

From the past few years the traffic control has turned into a serious issue for society. A variety of issues ranging from traffic blockage, absence of vehicle parking, pollution etc. have hassled humans. It has achieved major break in the recent era. However, the detection and classification of vehicles is a demanding concern. The scope in this area is huge because of the variety of challenging features that vehicles possess ranging from edges, colors, shadows, corners, textures, etc. Due to the progress in hardware and reduced manufacturing expenses, the amount of surveillance devices has risen in the past few years, and video cameras are of high resolutions used in these systems. As a result, large amount of video sources generates surprising volume of information that needs to be analysed and realized, but to examine the amount of information is too high for human operators. Therefore, researchers are more take the benefit in all probability from technology like Intelligent Transportation System [1, 2].

An important study of the surveillance system is the detection of different vehicle types. The main phase in traffic management software is the classification of vehicles. Prior information of the model and vehicle type is required, because it allows for queries as to know "which direction the vehicle has passed and at what time?". Therefore, feature extraction and classification of vehicles cover a vast scope of traffic management applications [3, 4]. Example images from a surveillance system are shown in Fig. 1.

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Fig. 1. Example images from a surveillance system

Yu Wang et al. 2019 [5], 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. 2018 [6], proposed an optimized Convolutional Neural Network architecture based on deep learning algorithms for vehicle detection and classification system used for intelligent transportation applications. PVANET as the base network, is selected and improved by fine-tuning to get better accuracy. It uses eight Concatenated ReLU convolution layers, eight inception layers as the base network and hypernet architecture is used to combine different levels of features, thereby making it better to achieve the desired bounding boxes for the Region Proposal Net layer.

In 2018, Velazquez-Pupo et al. [7] 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. Even though the best classifier is SVM, still they reported that the OC-SVM with an RBF Kernel has delivered the best results with a high performance and F-measure of 98.190% and 99.051% for the midsize vehicles. In the same year 2018, Murugan and Vijaykumar [8], 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 Harrish corner detector, which are used to classify the vehicles.

Ahmad Arinaldi et al. 2018 [9], presented a traffic video analysis system based on computer vision techniques. The core of such system is the detection and classification of vehicles for which they developed two models, first is a MoG + SVM system and the second is based on Faster RCNN, a recently popular deep learning architecture for detection of objects in images. They reported that Faster RCNN outperforms MoG in detection of vehicles that are static, overlapping or in night time conditions. Also, Faster RCNN outperforms SVM for the task of classifying vehicle types based on appearances.

In 2017, Audebert et al. [10] 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 process detection and classification of vehicles depending on a virtual detection zone was suggested by Seenouvong et al. 2016 [11], which comprises of foreground extraction, detection, feature extraction and classification. A Gaussian Mixture Model (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 2015, Dong et al. [12] 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. In the same year, Banu et al. [13] have recommended Histogram of Gradient feature extraction technique and morphological operations for better detection rate.

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 concludes the review.

2 Methods Used for Vehicle Detection

In the steps of processing of video, the initial stage is the image localization or detection of vehicle. Vehicle detection that includes expression of motion, tracking and behavior analysis which are the basis for further processing to achieve classification success rate [14]. There are two approaches in vehicle detection, one is appearance based and the other is motion based [15]. Parameters such as texture, color, and shape of a vehicle are considered for appearance based approach. Whereas, the moving characteristics are used to differentiate the vehicles from the static background scenes in motion-based approach.

2.1 Motion-Based Features

In computer vision technology, Motion detection is a significant job. The important characteristic of interest in traffic scenes is only the moving vehicles are of interest. In Motion detection technique, the foreground objects which are in motion are set apart from the still background of an image. For differentiating the moving traffic from the stationary background, the motion indications are utilized and they can be divided into: temporal frame differencing approach [16] which considers past two or three successive frames, a background subtraction approach [17] to construct background model by using frame history and the instantaneous pixel speed on the image surface is used by optical flow approach [18].

2.1.1 Frame Differencing

In temporal frame differencing technique, the difference in the pixels is calculated among two consecutive frames. Whereas, using a threshold value the moving foreground region are found out. The detection rate is improved by using three consecutive frames, where to obtain the moving target region the dual inter-frame subtraction is considered and binarized proceeding the bitwise AND operation [16].

2.1.2 Background Subtraction

Motion detection is found out using background subtraction approach which is the most studied and used approach. Using the difference of pixels among the current and background images, the foreground objects are extracted [17]. The background image is built using a recognized background averaging model, where sequences of images are averaged [19]. Though, the background is varying in actual traffic scenes; hence, this type of strategy is not appropriate for live traffic scenes.

2.1.3 Optical Flow

The rapid change of the instantaneous pixels on the surface of images resembles the moving objects in three-dimensional space in this approach. The primary concept is to use temporal and gradient data to equalize the pixels between the image frames. In [20], the problem of merged blobs of vehicles is resolved by dense optical flow approach. In [18], for vehicle segmentation, optical flow through 3-D wireframes is used. At the cost of additional computational time, accurate sub-pixel motion vectors are provided by the iterative nature of optical flow calculations. However, optical flow techniques are quite acceptable for vehicle detection because they are receptive to occlusion problems to a smaller extent.

2.2 Appearance Based Features

In terms of color, texture and shape, the stereo vision of an object can be classified. Methods based on these features usually uses prior data for modeling. It compares the derived two-dimensional image features to the real world three-dimensional features by using the feature extraction method. Unlike motion-based approaches, appearance-based approaches can distinguish fixed objects and detect them [21].

2.2.1 Part Based Model

In this approach, the objects are divided into several smaller parts and modeled in part-based detection models. Using the spatial differences between these parts, has proved to be very widespread method for vehicle detection. To improve the vehicle detection rate and resolve the occlusion problem, the vehicles in the image is divided into front, side, and rear parts [14]. For robust vehicle detection, the trained deformable part model is used [26].

2.2.2 Feature Based Method

The vehicle's visual appearance is defined by encoded representative feature descriptions. Various characteristics such as local symmetry edge operators have been used in car detection. But it is vulnerable to differences in size and illuminance; therefore, an edge-based histogram of more spatial invariances is used [22]. These simple characteristics develop into more general and robust features which directly detect and classify vehicles. In vehicle detection literature, the Scale Invariant Feature Transformation [23], Oriented Gradient Dimension Histogram [24] and Haar-like Features [25] are included.

2.3 Neural Networks

There are six major stages in the vehicle detection through neural networks. They are loading the data set, designing the convolutional neural network, configuring training options, training the object detector using Faster R-CNN, and evaluating the trained detector. The above processes are discussed as follows.

2.3.1 Regions with Convolutional Neural Network Features (R-CNN)

There are two basic concepts, Regional proposals and CNN which are combined in R-CNN method. The region proposals are made to locate and dismember objects following bottom to top approach. If there is inadequate label training data, supervised training will be followed for a field-specific fine-tuning process, which in turn offers substantial progress. Hence it is named as R-CNN as they combine Regional proposals along with CNNs [27].

2.3.2 Faster Regions with Convolutional Neural Network Features

A new and popular approach is to use deep convolutional neural networks that can learn discriminative features directly from the input images for a specified task in a supervised manner. The deep convolutional neural network uses many layers of convolution filter sets that learn a hierarchical representation of the input image data, where lower level convolutional layers will learn to detect simple features such as lines and textures, while higher level convolution allayers will learn features that are combinations of the lower level features [9].

Due to poor lighting and weather conditions, background noise, traditional image-based detection methods for traffic scenes have trouble obtaining good images. Some of the images captured in different weather conditions are shown in Fig. 2. A new technique was proposed by Nastaran Yaghoobi Ershadi et al. 2018 [28] for precisely segmenting and tracking of vehicles. Hough transform is used for extracting road outlines and lanes, after removing the perspective using Modified Inverse Perspective Mapping. GMM is then used to separate moving objects and also a chromacity based operation is applied to resolve the shadow effects of vehicle.

An adaptive threshold termed as the triangle threshold method was proposed by Mohamed A. El-Khoreby et al. 2017 [29] for background subtraction algorithm. The entire process comprises of four phases: background modeling, difference histogram, thresholding and post processing. The approximate median filter is used for background modelling and the triangle threshold is applied on the histogram variance of the background model and the current frame. Eventually, to increase the detection efficiency, some morphological operations are performed. Xuerui Dai et al. 2016 [30] adopted the

Fig. 2. Left images: images in fog. Right images: images in night.

Viola and Jones's sliding-window and Aggregated Channel Features for vehicle detection. Upon extracting the image features, a regular AdaBoost classifier is trained as a strong classifier and decision trees as weak learners.

3 Methods Used for Vehicle Classification

The focus of Vehicle Classification System is to categorize vehicles into different classes like car, van, truck, bus, etc. In conjunction with distinct classification approaches, a range of geometry, texture and appearance-based feature extraction methods are developed.

3.1 Geometry-Based Approaches

In 2000 and 2002, Gupte et al. [31, 32], have used a fixed camera for vehicle classification to concentrate on the highway images. In vehicle classification, the length and height of rectangular patches including vehicle blobs are used as features. However, they confine the work on the classification of vehicles into two classes (cars and non-cars and trucks or non-trucks) on the basis of height and length. Even though the classification was based on the Region of Interest features, it may not be possible to obtain a fine classification of vehicles.

3.2 Appearance-Based Approaches

In this approach, to classify the vehicles the features depending on edges, gradients, corners are used. Buch et al. 2009 [33] have suggested appearance based features like 3D-HOG [34], which would identify vehicle models depending on 3D models and also perform model-based matching for classification of vehicles. Morris and Trivedi used simple vehicle blob features [35] after transformation through Fisher's Linear Discriminant Analysis. The weighted k-Nearest Neighbor classifier is utilized to classify eight different types of vehicles, such as Bike, Sedan, Van, Pickup, SUV, Truck, Merged, and Semi.

3.3 Approaches Based on Texture

Texture is one of the major class of discriminatory image feature. Several works in the field of computer vision, texture-based features have been used [36]. Zhang et al. [37]

used texture based descriptors called as Multi Block Local Binary Patterns and multi-branch regression trees dependent AdaBoost classifier. The fundamental Local Binary Pattern creates a binary string for each pixel, by considering a window size of 3×3 neighbourhood pixels.

3.4 Mixed Approaches

In the process of describing vehicle types, Xiaoxu Ma and Grimson [38] used implicit and explicit edge shaping models and Scale-Invariant Feature Transform and for classification purpose, a two class Bayesian Decision Rule is used. In order to distinguish between the categories of vehicles of different sizes, the geometrical features like area, width, aspect ratio and rectangularity are considered [39]. In addition, the vehicle within a specific form of size is centered on shape-invariant picture scenes [40] and statistical characteristics based on texture parameters, like variance, mean, skewness, and pixel entropy for key vehicle blobs. Classification shall be performed at two levels using the K-Nearest Neighbor Classifier (k-NN) in each class. At the initial stage, a k-NN calculates the size and in the next stage, the vehicle type is predicted. Furthermore, an adaptive k-NN is utilized for the classification vehicle as small or big, and then in a classification of car or motorcycle (if small) or a class of bus or truck (if large). Indeed, they found that the use of such geometric features could actually cause confusion while distinguishing a bus or a truck because of similarity in heights, widths or lengths. Comparison of different approaches for Vehicle classification and their success rate are shown in Table 1.

Table 1. Comparison of different approaches for Vehicle classification

Reference	Approach	Classification success rate
Yu Wang et al. 2019 [5]	Improved spatio-temporal sample consensus algorithm	97.8%
Chia-Chi Tsai et al. 2018 [6]	Optimized Faster R-CNN	90%
Fukai Zhang et al. 2018 [41]	DP-SSD	77.94%
Velazquez-Pupo et al. 2018 [7]	OC-SVM	99.051%
Murugan and Vijaykumar 2018 [8]	Adaptive neuro fuzzy inference system classifier	92.56%
Ahmad Arinaldi et al. 2018 [9]	MoG + SVM, Faster RCNN	54.5%, 67.2%
Nicolas Audebert et al. 2017 [10]	Convolutional Neural Network	67% & 80%
Seenouvong et al. 2016 [11]	K-Nearest Neighbor Classifier	98.53%.
Dong et al. 2015 [12]	Semi-supervised convolutional neural network	96.1%

4 Database

In [42] they collected the vehicle database from the Vision-Based Intelligent Environment project and available in [43] which comprises single camera per lane and the proposed system identifies only one vehicle per frame. Moreover, to identify multiple vehicles per frame, it is easier to extend the system. Two distinct data sets of vehicles are used in [27]. The first dataset consists of 350 pictures [44] and secondly 1000 pictures from the available vehicle data set [45]. The images contain one or two samples of a marked vehicles in each of these datasets. Each picture involves one or two labeled vehicle samples in these datasets. The R-CNN and Faster R-CNN deep learning techniques have been used to train the vehicle detector using sample vehicle datasets.

In [7], the efficiency of the suggested method is verified on traffic videos which are recorded in Guadalajara, Mexico. Along with these it is also tested on GRAM Road-Traffic Monitoring dataset [46] and videos recorded in Britain's M6 motorway [47]. The example images from the dataset are presented in Fig. 3. In order to reduce the computation time, all videos are brought down to 420_240 pixels at 25 fps and down sampling is done.

Fig. 3. The example images got from GRAM-RTM dataset

In [48] have established a vehicle dataset named as BIT-Vehicle Dataset that consists of 9,850 vehicle images to test the suggested technique. In the whole dataset, the proportion of night light images are about 10%. Figure 4 demonstrates some examples of images taken at distinct moments and locations from two cameras. The images show changes in lighting conditions, viewpoint, vehicle surface color, and scale. Due to the size of vehicle and delay in capturing, the bottom or top portions of certain vehicles are not included in the dataset.

The Fig. 4 shows, one or two cars will appear in one picture and each is annotated beforehand. It separates all vehicles into six types in the dataset: Sedan, SUV, Bus, Microbus, Truck, Minivans. DETRAC data set is used in their work [28] which consists of 10 h of videos captured at 24 different locations in China. The videos are recorded at 25 frames per second in different lighting conditions day traffic, occlusion and intersection, with a resolution of 960 × 540 pixels. The dataset includes vehicle types of bus, car, van, etc., which are shown in Fig. 5.

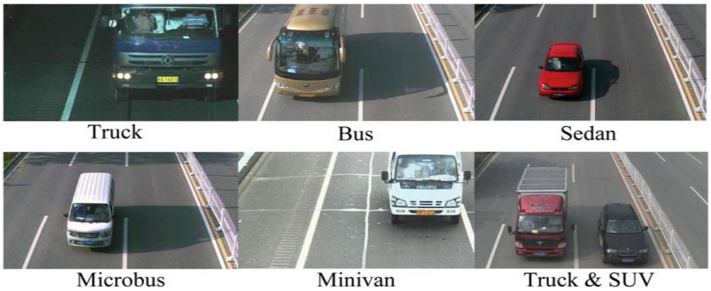

Fig. 4. Example of BIT-Vehicle Dataset

Fig. 5. Example of vehicle images in DETRAC dataset

5 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.

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