Southeast-Asian J. of Sciences, Vol. 6, No. 1 (2018) pp. 56-65

A VIDEO-BASED VEHICLE DETECTION AND CLASSIFICATION SYSTEM USING CASCADE HAAR CLASSIFIER

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Abstract

Vehicle classification data are imperative inputs for traffic operation, pavement design, and transportation planning. Automated traffic data collection and surveying can be a great tool in site selection, engineering, and more. A vigorous and real-time implementation is a challenge, however, especially in cases of high occlusion and a cluttered background. All these facts illustrate that vehicle data are extremely important for the rigorous analysis of traffic safety, traffic pollution, and flow characteristics. Unfortunately, most traffic sensors such as single-loop detectors presently in place cannot directly measure vehicle volumes. Though dual-loop detectors can measure classified vehicle volumes, a few of them is used in the current transportation systems to meet the practical needs. Seeing that traffic surveillance cameras have been increasingly deployed for monitoring traffic status on dominant roadways, effective utilization of these cameras for vehicle data collection is of practical significance. An important step towards attaining automated roadway monitoring capabilities is to detect vehicles in videos. The challenges lie in being able to reliably and rapidly detect multiple small objects of interest against a cluttered background which usually consists of trees and buildings, and then classify them as the light vehicle or heavy vehicle based on their

Key words: Intelligent Transportation Systems, Vehicle detection, Vehicle classification, Real-time surveillance, Haar classifier.

pixels length. To this end, we present a concept of traffic monitoring system. The proposed approach can disclose and classify vehicles using the uncelebrated video images. This prototype system is capable to use the uncelebrated surveillance cameras for real-time traffic data collection. The system also counts the number of cars passing in either direction in each frame. The car detection and classification is done using a cascade of Haar features.

1. Introduction

The comprehensive building block of the surveillance systems is the object classification which significantly impacts the reliability of its function (e.g., the public safety application and video indexing/tagging, video semantic search). The outdoor environments are more challenging for objects due to the following reasons (a) intractable environment conditions (e.g., fog, rain, lighting, and haze) (b) incomplete appearance details of moving objects due to closure, (c) large distance between the camera and the moving objects, (d) very low image resolution, since the moving object employs a small area (~ 50 squared pixels) in the video frames [1]. In this paper, an efficient vehicle detection and classification scheme is proposed which is based on Haar classifier. The proposed method is effective and simple to detect and classify moving vehicles. The rest of this paper is categorized as follows. Section 2 gives a concise description of the related research. Section 3 describes the new method of moving object detection scheme. Section 4 shows the experimental results and analysis of the proposed method. Section 5 concludes this paper.

2. Related Research

A hot focus of research in Intelligent Transportation Systems (ITS) over the last decade is the utilization of image processing technologies for vehicle detection. The previous vehicle detection and classification methods have been widely used in today's traffic detections and surveillance around the world. Modern investigations into vehicle classification via computer vision have occurred. Vehicle classification based on optical flow cannot detect the exact contour of the moving object and it is sensitive to the noise [2].

Vibha et al. [3] demonstrated that accurate vehicle dimension estimation could be performed through the use of a set of coordinate mapping functions. Although they were able to estimate vehicle lengths, the accuracy of vehicle classification is only 10%. This method requires camera calibration in order to map image angles and pixels into real-world dimensions.

Similarly, commercially available Video Image Processors (VIPs), such as the Video Track System developed by Peek Traffic Inc., are capable of vehicle data collection. The image-based technique was proposed in [4] identify only if there is a single object in the input video frame, but cannot classify the vehicles and need large computational time.

However, the cost for such systems is symbolic and they require calibrated camera images to work correctly. Calibrating these systems normally requires very specific road surface information (such as the distance between recognizable road surface marks) and camera information (such as the ascent and tilt angle) which may not be easy to obtain. Furthermore, recent studies [5] evaluating some of these commercial systems found that shadows and head-light reflections generated significant problems of false positives and early detections.

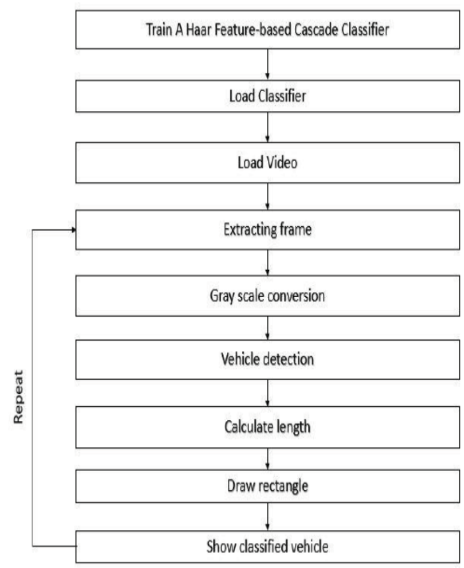

Fig. 1. The algorithm of the proposed method

The Proposed Method

The proposed method for vehicle detection and classification from the surveillance video has six steps which are shown in Fig. 1 and described in the following sections.

3.1 Train a Haar feature based cascade classifier

First, a classifier (namely a cascade of boosted classifiers working with Haar-like features) is trained with a few hundred sample views of a distinct object (i.e., a face or a car), called positive examples, that are scaled to the same size (say, 20×20), and negative examples - random images of the same size.

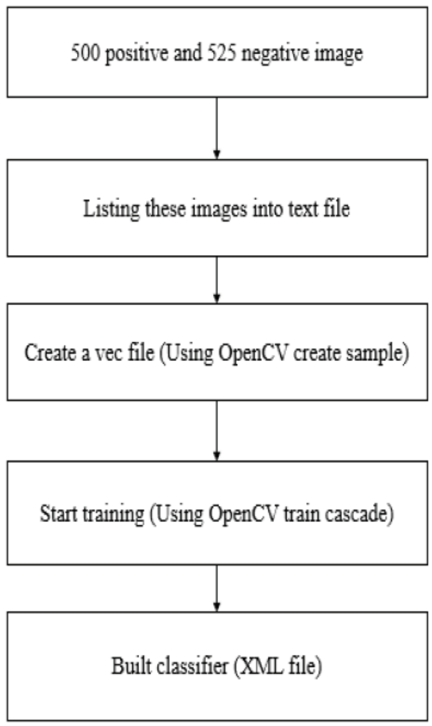

Fig. 2. The training procedure of the classifier

The training procedure is shown in Fig. 2. The classifier is invented so that it can be easily "resized" in order to be able to search the objects of interest at different sizes, which is more productive than resizing the image itself. The decision-tree classifiers are the basic classifiers with minimum 2 leaves. Haar-like features are given as the input to the basic classifiers and are calculated as described in [6]. The current algorithm uses the Haar-like features.

3.2 Load classifier

Train a standard classifier is the first step of the work. Then the classifier is loaded in OpenCV.

3.3 Load video

A suitable video taken from the uncalibrated camera is now loaded for further processing. A frame of an inputted video is shown in Fig. 3.

Fig. 3. A frame of an inputted video

3.4 Extracting frame

The video is a sequence of the frame. These frames are extracted from input video. An extracted frame from this video is shown in Fig. 4.

Fig. 4. The extracted frame from the video

3.5 Grayscale conversion

To detect a vehicle from the video frame, it is necessary to convert the video to grayscale. Images of this sort, also known as black and white, are completely composed of shades of gray, varying from black at the weakest intensity to white at the strongest. If each color pixel is characterized by a triple (R, G, B) of intensities for red, green, and blue, then the lightness method averages the most outstanding and least outstanding colors:

$$(max(R, G, B) + min(R, G, B))/2 \tag{3.1}$$

The average method simply averages the values:

$$(R + G + B)/3 \tag{3.2}$$

The more sophisticated version of the average method is the luminosity method. It also averages the values, but it makes a weighted average to justify the human approach. We are more sensitive to green than other colors, so green is weighted most massively [7]. The formula for luminosity is

$$0.21R + 0.72G + 0.07B \tag{3.3}$$

The color image cannot be used to detect the vehicle. A video is divided into hundreds of frames and then each frame of the video image is converted into the grayscale image. The frame shown in Fig. 4 is converted to the grayscale image as shown in Fig. 5.

Fig. 5. The grayscale converted frame

3.6 Vehicle detection

After a classifier is trained, it can be applied to video frames extracted from the input video. The classifier outputs a '1' if the region is likely to show the object (e.g., car) and '0' otherwise. To search for the object in the whole image, one can shift the search window across the image and check every location using the classifier. The classifier is designed so that it can easily find an object of an unknown size in the image. The scan procedure should be done several times at different scales [6].

3.7 Length calculation

The height and width of each detected object (vehicle) are calculated using the following equation:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{3.4}$$

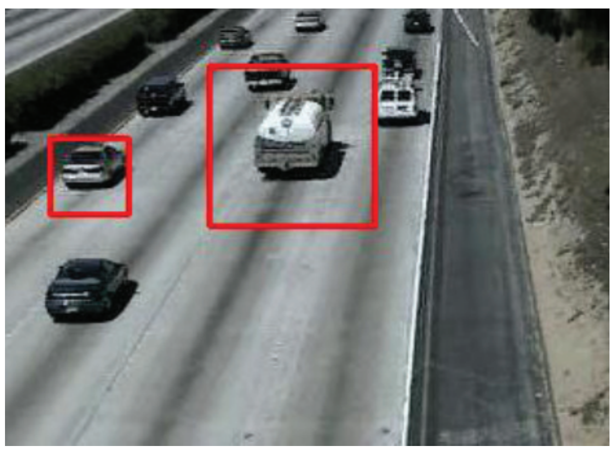

Fig. 6. Vehicle detection and rectangle drawing

3.8 Rectangle drawing

According to the calculated length, a rectangle is drawn using RGB color on each detected object as shown in Fig. 6.

3.9 Vehicle classification

A threshold value is set to differentiate the vehicle as the light or heavy vehicle. If the height and width of the rectangle are below the threshold value, then it is classified as the light vehicle otherwise the heavy vehicle. This classification process is shown in Fig. 7.

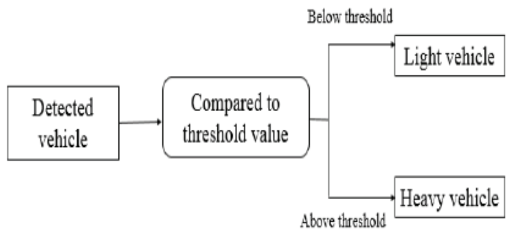

Fig. 7. The vehicle classification process

4 Performance Analysis

This section gives a brief description of the experiments performed on the video sequences captured by a low-end camera and the comparative analysis of the proposed method.

Fig. 8. (a) Vehicle detected, and (b) vehicle classified as heavy

4.1 Experimental results

All experiments are done on Intel Core i3 2.10 GHz processor with 2 GB RAM under Visual Studio 2010 and OpenCV 2.4.9. In the experiments, the images with size 325×240 pixels are used. The complete testing database consists of several surveillance videos taken from the three test locations.

Each video frame is taken from the video input and checked whether any vehicle exists in the frame. If so, then it is marked by drawing a rectangle.

Then the length of each rectangle is calculated and compared to the threshold value and finally classified it as the light or heavy vehicle as shown in Fig. 8.

4.2 Comparative analysis

The number of detected and correctly classified vehicles in the different rounds for an input video is given in Table 1. After vehicle detection, the accuracy of the vehicle classification is calculated and also stated in Table 1.

Table 1. Experimental results of vehicle detection and classification

Frame no. per round (30)	No. of vehicles	No. of detected vehicles	No. of classified vehicles	Success rate
Round I	4	4	4	100%
Round II	3	3	3	100%
Round III	Nil	Nil	Nil	Nil
Round IV	5	5	4	80%
Round V	4	4	4	100%

5 Conclusion

For reliable detection and classification of the vehicle, it is necessary to set up an embellished information platform and improve the quality of the transportation management system. However, classified vehicle volumes are not directly measured by the ubiquitously deployed single-loop detectors. To better utilize, the proposed method is more efficient. It combines several robust algorithms to lighten the negative impacts from shadows, slight camera vibrations, and vehicle occlusion in the horizontal direction. The evaluation results from the three test locations are encouraging. The accuracy of vehicle detection and classification is above 97% for all the three test sites. The test results indicate that the proposed VVDC system worked stably and effectively in the tested traffic conditions. In the future, this work can be extended to get relevant information from the video of the calibrated cameras such as detect vehicle in the blurred image, classify the vehicle that is in long distance from the camera and the angular orientation of the camera.

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