Vehicle Modeling and Detection in Crossroads

Tai-Hung Lin and Chih-Wen Su
Chung Yuan Christian University, Taiwan

***Abstract*—In this work, we proposed a novel method to detect vehicle automatically under different field of view in urban area. First, traffic flow maps are reconstructed to estimate the size and orientation of a vehicle for every position. Vehicle models are then represented by flow information and foreground blob which shows the potential appearance of a vehicle in each position in the crossroad. Finally, we perform a voting strategy to detect the potential vehicle. The experimental results show the robustness of our system. Our algorithm can be applied to the surveillance cameras with different view in crossroads.**

I. Introduction

WITH the development of smart city, the study on Intelligent Transportation Systems (ITS) attracts a large number of researchers. The autopilot control systems, driving assistance systems, traffic surveillance systems and many traffic-related issues have become hot topics in recent years. Vehicle detection is one of the fundamental functions in many ITS applications. There are numbers of sensors can be used for detecting vehicles including radars, ground loops, Infrared sensors, RFIDs and cameras. Due to the non-intrusive nature and high flexibility of surveillance cameras, they always play important roles for monitoring the traffic in urban environments. However, since each individual camera has its own field of view, it is also hard to detect vehicles in the captured video without any manual settings.

To adapt to the complex traffic situations in urban environment, it is essential to reconstruct the road area and traffic flow patterns for individual camera automatically. If we understand the traffic flow patterns, we can have more information to help the detection or tracking of vehicles. In this paper, we propose a method to reconstruct the information of road area and traffic flow patterns. We also model the size and pose of a vehicle according to its position on the video frame, to tolerate the perspective distortion caused by camera view.

II. Related Work

Many vehicle detection methods have been proposed in last decade. In general, these studies can be classified into two categories: foreground-based approaches and training-based approaches. In order to identify vehicles, many characteristic features are used as description. In [1], color and brightness distortion were utilized to identify vehicle area, and then median filter and morphological filter were used to eliminate the noise. Wu *et al*. [2] normalized the image by histogram extension to address complex weather conditions and segment moving object dynamically by gray-level differential value method (GDVM). Gangodkar *et al*. [3] extracted moving foreground objects by estimating block motion between frames. Compared with the color/intensity thresholding and frame difference, Gaussian Mixture Model (GMM) is a more common way to model the color distribution of background and extract foreground object. He *et al*. [4] proposed Gaussian mixture model with confidence measurement (GMMCM) for vehicle detection in complex urban traffic scenes. However, foreground-based approaches usually detect moving objects instead of detecting "vehicles", which means these approaches may not be able to identify whether a detected object is a vehicle or not. On the other hand, training-based approaches extract local features from training images and then train a classifier for detecting "vehicle-like" objects on video frames. Although training-based approaches are able to identify vehicles on video frames, they may also have a large number of miss-detections at the same time. Since each camera has its own field of view, the appearance of a vehicle can be different in the videos captured from different cameras.

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Therefore, we propose a vehicle detection method without any camera calibration and manual settings. By modeling the vehicles and traffic flows in statistics, our proposed system can automatically perform vehicle detection to the videos captured from the general traffic cameras mounted on high poles or masts.

III. Proposed Metohd

Our proposed system contains two major parts: traffic flow/vehicle modeling and vehicle detection as shown in Fig. 1.

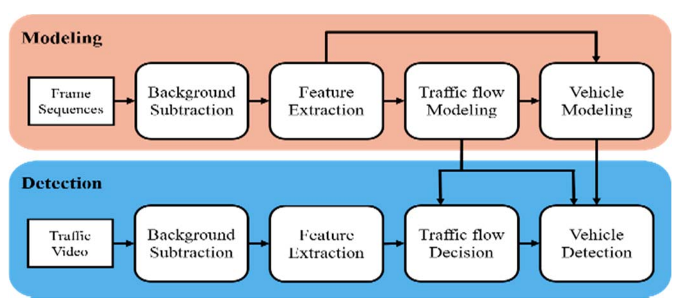
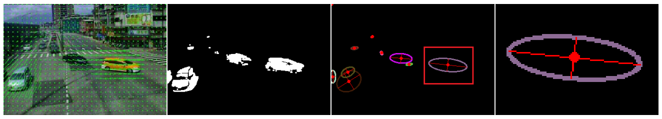


Fig. 1. Flow chart of the proposed system.

A. Traffic flow/vehicle modeling

There is usually only single traffic flow pattern in highway environment. On the contrary, there are T-junctions、crossroads and other complex traffic flow patterns in urban traffic. In the offline modeling stage, we capture a short (15~25 minutes) and smooth traffic video from traffic camera at first. We apply GMM to extract foreground pixels from video frames and find dense motion fields using dense optical flow[5]. Each foreground blob is then fitted by an ellipse shape and we record the center, major axis and minor axis of it as shown in Fig. 2.

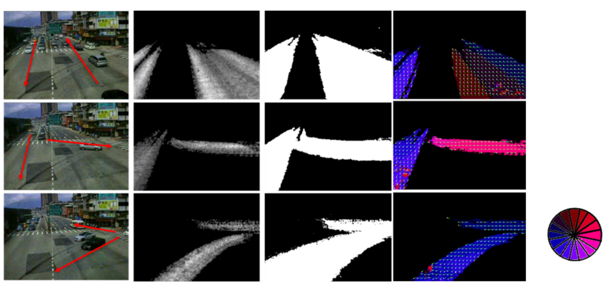


(a) (b) (c) (d)

Fig. 2. (a) Dense optical flow. (b) Foreground image extracted by GMM. (c) Fitting foreground blobs by ellipses. (d) The center, major axis and minor axis of an ellipse in (c).

We use median filter to find the standard lengths of major/minor axis of the vehicles at any position on video frames. Since the length of a vehicle is linearly increasing along its vertical position on a frame, we use RANSAC [6] to estimate the linear function of the ideal lengths of major axis and minor axis of a standard vehicle with specific orientation.

To model the traffic flow, we extract binary road map by thresholding the cumulative foreground map as shown in Fig. 3. The traffic flow map is determined by calculating the major orientation of the optical flows recorded at the same pixel location. Since the traffic flow of a crossroad is not always the same. It changes according to the switching of traffic lights. In this case, we split the traffic video into several segments and merge similar ones by considering the consistency of traffic flow. Once the segments are merged into groups, road area and traffic flow map of each traffic flow pattern are determined by the cumulative foreground map and major orientation of optical flows, respectively.

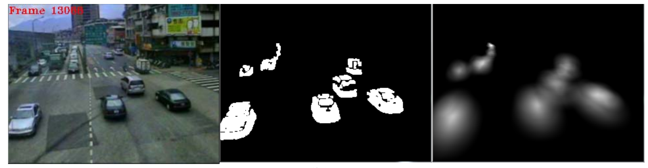


(a) (b) (c) (d)

Fig. 3. Each row represents a traffic flow pattern in the video. (a) Original traffic scenes. (b) Cumulative foreground maps. (c) Road maps. (d) Traffic flow maps. Colors denote the flow orientations

B. Vehicle detection

In the online detection stage, after extracting foreground pixels and dense motion field, we calculate the correspondence between current foreground motion and traffic flow maps. Once the corresponding traffic flow map is selected, each foreground pixel votes all of its neighboring pixels inside the corresponding ellipse as shown in Fig. 4. Then, the votes from the foreground pixel on the road map are accumulated for detecting the center of a vehicle. For each foreground pixel, we vote its neighboring pixels according to the corresponding ellipse range that determined in modeling stage. The weight of votes are normalized according to the ellipse area to ensure every votes have same weight. We use mean-shift algorithm [7] to find local maximums on voting image. Each local maximum is regarded as a detected vehicle on the frame.



(a) (b) (c)

Fig. 4. (a) Original image. (b) Foreground pixels. (c) Voting image.

IV. Detection Result

Fig. 5 shows some detection result of the proposed method at different crossroads. Each red ellipse denotes a detected vehicle on the frame. Our method can detect vehicles in different traffic flows without any manual setting. The average precision and recall are both achieve over 75% at crossroads.

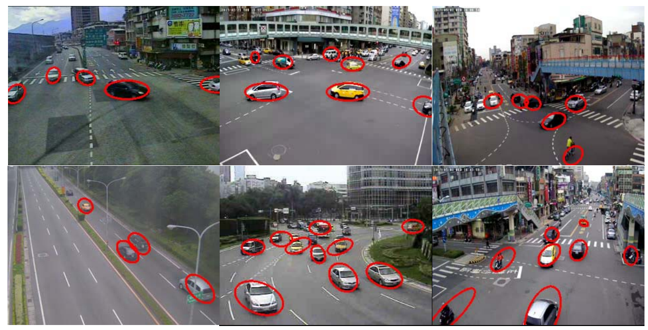


Fig. 5. Vehicle detection result.

V. Conclusion

In this work, we proposed an automatic vehicle detection scheme for traffic cameras. By modeling traffic flow patterns and the size/pose of a vehicle according to its position on frame, our system can be applied to general traffic cameras for vehicle detection task in complex traffic environments.

References

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