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Automatic vehicle classification and tracking method for vehicle movements at signalized intersections

C. Chai and Y. D. Wong

***Abstract*— This paper presents an automatic vehicle classification and tracking method to estimate the traffic parameters of vehicle movements at signalized intersections. Different from traditional methods, this classification and tracking system is based on a projective transformation of video frames. The proposed method has a good ability to classify detected vehicles and calculate parameters of vehicle movements at intersection area. Experimental results show the proposed method is more accurate and powerful than feature-based detection algorithm to tackle the problem of changing shape and size of vehicles due to turning movements. Based on tracking results, vehicle movements, including turning paths and speed profile are analyzed. The proposed method is a valuable tool for building path and speed control strategy of intelligent vehicles.**

I. INTRODUCTION

Cities around the world are looking for new answers to deal with perennial road traffic problems, such as traffic congestion and safety. Apart from building infrastructure systems, a more efficient solution is using intelligent technologies to control and manage road traffic, such as path and speed control schemes [1][2]. These schemes control vehicles' path and speed to adapt with road environments and to avoid collisions. As signalized intersections form one of the most common bottlenecks in the urban traffic system, the path and speed control system should be able to help drivers reduce their traffic delay and avoid vehicle conflicts at intersection area.

To build path and speed control schemes, sufficient data of traffic flow are necessary. However, manual data extraction involves large amount of time and manpower. Furthermore, the accuracy of manually extracted data is not always reliable. With the development of computation power, a lot of advanced technologies, including video image processing technique, have been being used [3]. Many vehicle detection and tracking programs are developed to automatically extract vehicle position and speed. However, current vehicle detection and tracking algorithms, which are not particularly designed for signalized intersections, have several limitations. In conventional vehicle tracking algorithms, vehicle position and speed are calculated. For vehicle classification, the most straight forward method is to use geometric features, length and width. However, as the camera is fixed at a certain height and angle, vehicle geometry features are changing with the position of vehicles as well as camera location. Detected sizes for the same vehicle at different time steps are always different. As some vehicles are turning at intersections, the sizes become even less well defined.

C. Chai and Y. D. Wong are with the Centre for Infrastructure Systems, Nanyang Technological University, 639798, Singapore (65-96544059; e-mail: chai0076@e.ntu.edu.sg, cydwong@ntu.edu.sg).

Due to afore-mentioned limitations, some classification algorithms are developed by using other criteria to separate different types of vehicles. Several approaches classified only two categories, cars and non-cars [4][5]. Other approaches consider movement parameters that include average speed, acceleration and deceleration rates and lateral drift [6] [7] [8]. Such methods are valid under free flow conditions but not suitable for congested flows and at signalized intersections. 3-dimensional feature-based detection is also used to classify vehicle types [9] [10]. One of the most successful algorithms removes the influence of vehicle position and identifies vehicle types, including cars, minivans, van truck and truck [11]. The algorithm is found to be accurate in detection and classification of vehicles at highway area with camera views from front or back of the vehicles. However, the detection model has not been tested at an intersection area, where vehicles are moving in different directions.

In this study, a vehicle classification and tracking algorithm is specially designed for vehicle movements at signalized intersections. Using transformed video, vehicle types are identified by calculating the length and width of each vehicle. Non-motorized transport, including pedestrians and bicycles, can also be classified. Changing of geometry features due to movement direction is removed by automatically calculating the motion vector of each moving object.

Based on automatic vehicle classification and tracking, path and speed profile of multi-type vehicles are collected in the mixed traffic flow at signalized intersections. The results can be used to analyze vehicle movements at the intersection area and to build an intelligent path and speed control algorithm for various types of vehicles.

II. AUTOMATIC VEHICLE CLASSIFICATION AND TRACKING

A. Structure of the method

In this study, the algorithm involves three stages, as shown in Figure 1. The first step is to estimate the position of video camera and transform co-ordinates of video frames into global co-ordinates. By using the transformed video, size of vehicle on the video frame will not be related to the distance from the camera's position. Next, optical flow method is applied to detect vehicles and record their position and size at each video frame. The algorithm is modified by removing shadows and automatically calculates moving directions and size of each detected vehicle. Vehicle type is identified based on defined range of vehicle sizes. Finally, traffic parameters, such as trajectory, speed profile and gaps between vehicles are calculated according to recorded data.

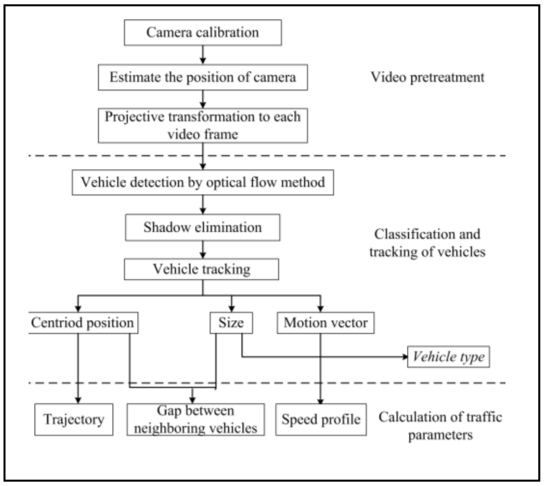

Figure 1. Procedure of vehicle classification and classification method

B. Camera calibration and projective transformation of video frames

To remove the impact of camera location on sizes of detected vehicle, co-ordinates of video frames (pixels) have to be changed into global coordinates (meters). Camera location needs to be estimated first. Camera calibration is conducted to map geometric elements, primarily road user positions, from image space to the world space. A toolbox developed using MATLAB is used to annotate the calibration data, find initial estimates, conduct the camera calibration and estimate camera location from recorded video [12] . The video records of traffic flows are taken on top of a tall building in the vicinity of a signalized intersection. The estimated camera position is shown in Figures 2 and 3.

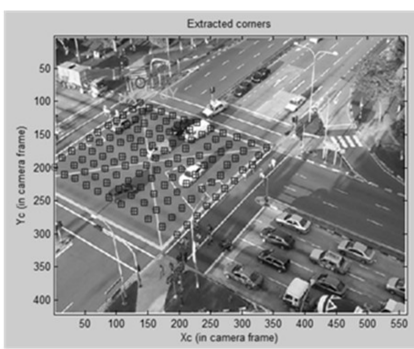

Figure 2. Estimated grid of rectangular target (intersection box area)

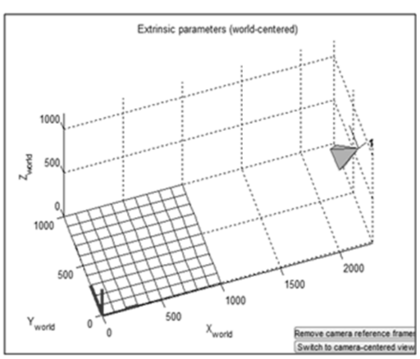

Figure 3. Estimated position of camera [12]

Corresponding control points are annotated in image and global space. The global coordinates are calculated from their positions on the global map [13]. Original video frame and transformed video frame are shown in Figures 4 and 5. The length of line segments is measured in video frames (Figure 6). The global length is measured using a road distance meter on-site. Several control points are selected on-site as distance between each pair of points is measured. By projective transformation of control points, the recorded video images can be transformed as orthographic frames. After the transformation, a global coordinate system can be created to transfer pixel values from the picture into global position. The geometry features of vehicles, length and width, will be close to constant.

Validation of calibrated data is based on comparison between real distance from on-site measurement and estimated distance from pixel values of calibrated video [14]. Crosswalk width (3m) is selected as reference distance. As shown in Figure 6, the difference in pixels is 34, then 1m equals to 12.13 pixels.

Figure 4. Recorded video frame at a signalized intersection

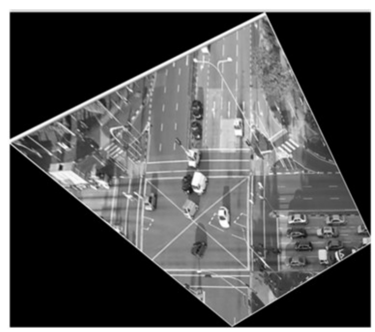

Figure 5. Transformed video frame

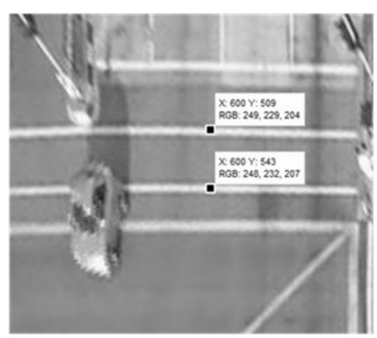

Figure 6. Reference distance (width of pedestrian crossing)

To transfer pixel values to global distances, several test cases (length of lane markings) are selected within approach and departure lanes. As taller objects will lead to larger parallax errors, hence all the samples are selected on ground level. A linear regression analysis is performed to test the relationship between estimated and true distances [15]. As indicated in Figure 7, the regression line used is y=x, which stands for estimated distance being equal to true distance. The results show a relatively small Mean Square Error (MSE) at 0.032. The coefficient of determination (R^2) is 0.9856 which is significant at 0.1% [16].On the other hand, the calibration results also show a larger error when true distance is larger, and this may be caused by an accumulation of small errors.

C. Automatic vehicle detection and classification

After the transformation, size of vehicles in the video frames is no longer related to the vehicle position. Then, features of different types of vehicles are detected and tracked using optical flow method provided in Computer Vision System Toolbox of MATLAB [17]. In this study, the existing toolbox has been modified to improve detection ability. First, changing of light condition is removed by automatically detecting the color of road ground. Shadow elimination is conducted according to the algorithm suggested by Hsieh et al. [11]. A trajectory filter based on (Kalman's method) is involved to link vehicle positions at neighboring video frames to form a continuous trajectory [18]. Moreover, to detect small objects including motorcycles and pedestrians, sensitivity of the original detection algorithm has been modified. With the add-on modules, accuracy of vehicle detection is much increased and the model is able to produce continuous trajectory automatically.

Vehicles are classified as Small Vehicles (private cars and taxi), Middle Vehicles (light good vehicles and minibuses), Large Vehicles (heavy good vehicle and bus), Motorcycles and Bicycles, and Pedestrians, as shown Table 1. Movement parameters of various types of vehicles are not considered in this algorithm because of vehicles average speed being much lower at intersection area than usual. Detection results of mixed traffic flow at signalized intersection are shown in Figures 8 with threshold video shown in Figure 9.

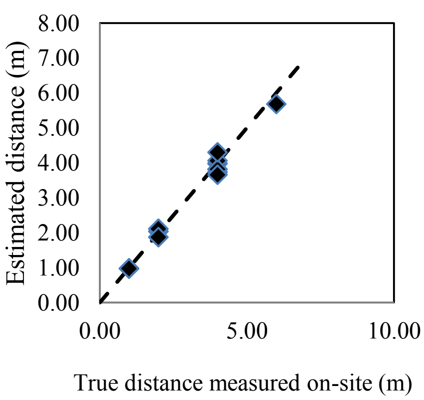

Figure 7. Error test of projective transformation

TABLE 1 RANGE OF GEOMETRY FEATURES TO CLASSIFY VEHICLES AND NON-MOTORIZED TRANSPORT

Vehicle type	Length (m)	Width(m)
Small vehicles (Private car, taxi)	3.0-4.5	1.2-2.0
Middle size vehicles (Light good vehicle, minibus)	4. 5-8	1.7-3
Large vehicles	8-15	3.0-3.0
Motorcycles and bicycles	1.4-3.0	0.4-1.2
Pedestrians	0.4-1.0	0.4-1.0

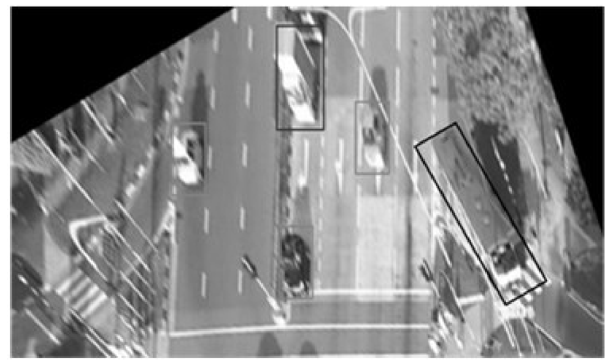

Figure 8. Detection results of mixed traffic flow at intersection approach

Figure 9. Threshold video (moving obstacles in white and background in black)

D. Calculation of traffic parameters

Using traditional data extraction methods, traffic parameters such as traffic density and vehicle speed are measured manually. Instead, by using automatic vehicle detection and tracking method, automatic recording and computation of such parameters are possible.

1) Global trajectory and distance traveled

Vehicle's global trajectory computed as position of the centroid of a vehicle is recorded in time order. The three-dimensional trajectory of a typical vehicle tracked is shown in Figure 10.

Distance travelled is estimated by a summation of distance between vehicle centroid in every pair of neighboring frames. Distance between two centroid in global coordinates $P(x_i,y_i)$ and $Q(x_i,y_i)$ is calculated as:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (1)$$

For n = total frames captured, i = 1 to n-1and j= i+1 to n, total distance travelled is given by:

$$D = \sum_{i=1,\, j=i+1}^{n-1,\, n} d_{ij} \quad (2)$$

2) Speed profile estimation

Motion vectors of every vehicle (v), which is the average velocity of each pixel within the vehicle as shown in Figure 11, are recorded in vehicle detection and tracking system. Therefore, estimated speed of a vehicle is calculated as:

$$v_1 = v \quad (3)$$

On the other hand, average speed of a vehicle travelled can also be computed by changes of its position:

$$v_2 = d_{ij} \times fps \quad (4)$$

where fps is the frame rate of input video (number of frames in each second). A speed profile of a typical vehicle tracked is shown in Figure 11.

3) Front and rear gap

The position, size and motion vector of each detected vehicle is recorded. Front and rear gap (G) is calculated as the distance between two centriods (D) minus the part inside the outline of detected vehicles (S), as shown in Figure 12.

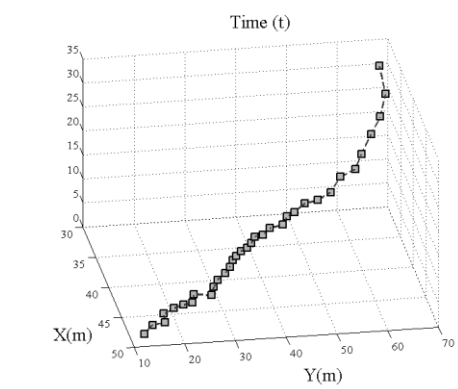

Figure 10. Trajectory of a typical tracked vehicle

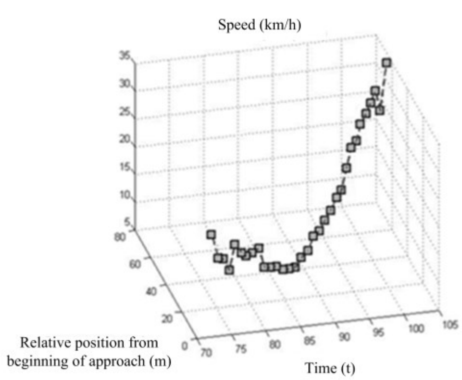

Figure 11. Speed profile of a vehicle tracked

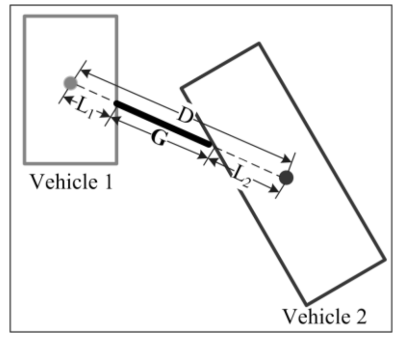

Figure 12. Front or rear gap between vehicles

D. Results and discussions

In order to analyze the performance of proposed method, 2 videos of different intersections are used. The duration of each video is 20min (30,000 frames). Comparison of manually extracted and automatically detected traffic volume of different types of vehicles is summarized in Table 2. According to the error test, the proposed vehicle detection and classification method is accurate at signalized intersection. The errors are due to missed or over-segmented (two closed vehicles are detected as one) vehicles. For example, one missed vehicle in a sample of 100 vehicles will lead to 1% error. Accuracy in classification of Small Vehicle, Middle Vehicle and Large Vehicle are acceptable.

III. VEHICLE MOVEMENTS AT SIGNALIZED INTERSECTIONS

A. Two-dimensional movements and turning path

At signalized intersections, right-turn and U-turn vehicles track curved trajectories and have speed in two-dimensions (both in x and y directions) while noting that vehicles drive on left side of roads in Singapore. Observations revealed that vehicles passing straight-through the junction did not display much lateral drift while left-turn vehicles moved within the slip road. Therefore, to study the two-dimensional movements of right-turn and U-turn vehicles, observed trajectories of both movements at a field site are plotted, as shown in Figures 13 and 14.

According to Figure 13, right-turn paths of different types of vehicles (including motorcycles) are similar. However, in Figure 14, an obviously smaller turning radius of motorcycles' U-turn path (in dotted line) can be identified.

TABLE 2 ACCURACY COMPARISONS OF VEHICLE DETECTION AND CLASSIFICATION

	Vehicle type	Actual	Detected	Accuracy
Video No.1 (1400 pcu/h)	Small Vehicle	2273	2043	89.88%
	Middle Vehicle	1111	893	80.38%
	Large Vehicle	321	294	91.59%
	Motorcycle and Bicycle	560	459	81.96%
	Pedestrian	1847	1149	62.21%
Video No.2 (800 pch/h)	Small Vehicle	973	857	88.08%
	Middle Vehicle	387	336	86.82%
	Large Vehicle	306	290	94.77%
	Motorcycle and Bicycle	639	459	71.83%
	Pedestrian	1035	849	82.03%

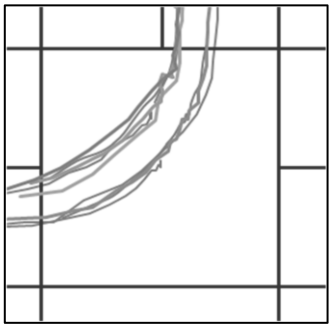

Figure 13. Observed trajectory of right-turn vehicles (all type)

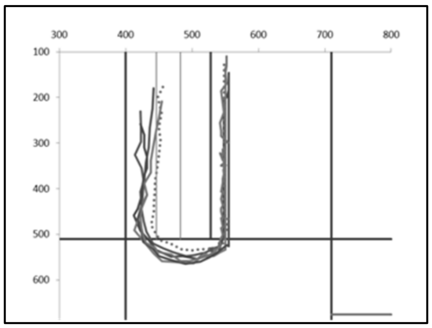

Figure 14. Observed trajectory of U-turn vehicles (all type)

B. Speed profile of vehicles

From vehicle tracking, time history of vehicle speed is calculated. The formula uses 2 neighbouring positions of one vehicle, 2 from x-coordinate and 2 from y-coordinate, in order to find the difference between Position-1 and Position-2 so that the speed can be obtained. Vehicles moving through the intersection are further classified into three groups based on their situational movement behaviour.

1) Non-stopping vehicle

Vehicles entering at green phase do not stop at the stop-line, and these vehicles are classified as non-stopping vehicles. As vehicles turning right always have a larger deceleration and lower speed than those moving straight-through, vehicles moving straight-through always pass through the junction within a shorter time interval. It is found that a non-stopping vehicle speed is affected by the relative time with respect to the beginning of green phase. There are two possible speed profiles for vehicles moving straight-through direction. For Case I, the subject vehicle entered the junction area at the beginning of green phase, and did not slow down (see Figure 15). On the contrary, a slight acceleration is detected. In Case II, the tracked vehicle entered junction area in the middle of green phase (26th of total 85 time steps of green phase, 1 time step = 0.4s) and cleared the junction area before the green phase ended (Figure 16). From speed-time history, the vehicle is moving at a relatively slower speed than Case I and shows a small deceleration before it reached stop-line (84th time step). After crossing the stop line, acceleration was detected.

2) Stopped vehicle

Vehicles, which are forced to stop during red phase, are classified as stopped vehicles. The subject vehicle illustrated in Figure 17 was moving in a straight-through direction at the signalised junction. Upon moving closer to the stop-line during red phase, it decelerated. Then, after stopping and waiting at the stop-line for a while, this vehicle accelerated and moved forward to junction-box area on green.

3) Slowed-down vehicle

Some vehicles that arrived towards the end of red phase did not stop fully. Such vehicles slowed down before the stop-line and accelerated after the onset of green phase, as shown in Figure 18. Compared to Case II of the non-stopping vehicle, slowed-down vehicles arrived at red phase.

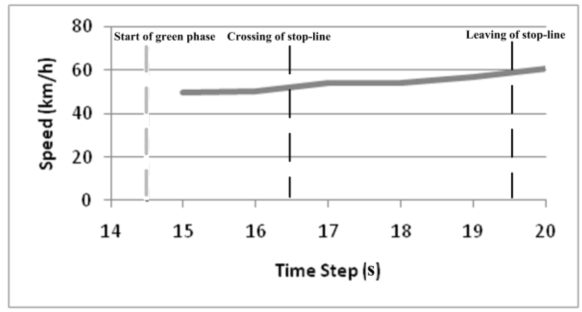

Figure 15. Speed profile of a typical non-stopping vehicle entering at the early part of green phase (Case I)

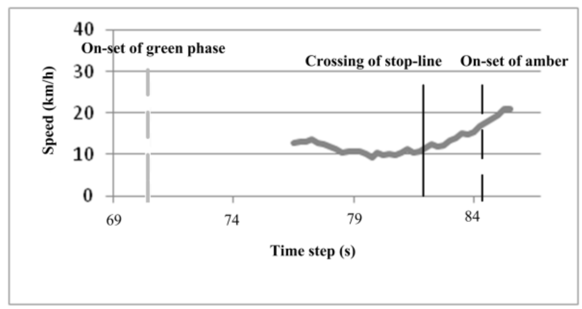

Figure 16. Speed profile of a typical non-stopping vehicle entering in the middle of green phase (Case II)

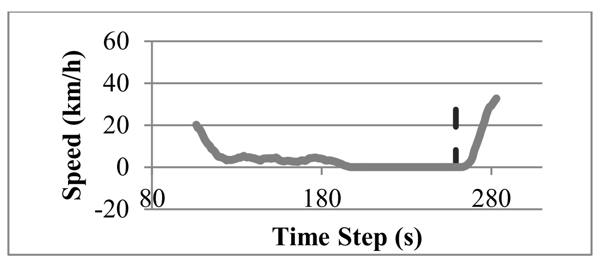

Figure 17 Speed profile of a stopped vehicle

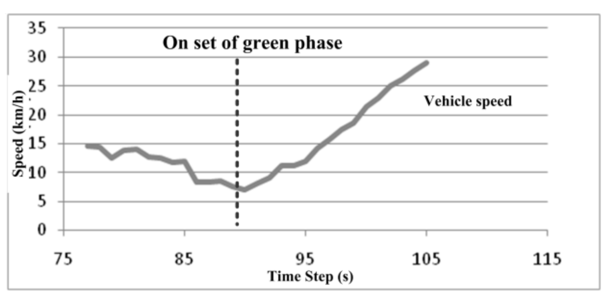

Figure 18. Speed profile of a slowed-down vehicle

IV. CONCLUSIONS

In this paper, an automatic vehicle classification and tracking method to estimate traffic parameters of vehicle movements is proposed. The method is specially designed for signalized intersection area as it is powerful and accurate to deal with the changes of vehicle shape and size. Based on a projective transformation, global co-ordinates are applied to each video frame. Classifier is designed based on size of vehicles instead of features to accurately separate vehicles into different categories. Several features, including vehicle position, type, size and speed can be automatically extracted. Then, vehicle's two-dimensional movements and speed profiles are used to analyze traffic parameters of vehicle movements at signalized intersections. The contribution of proposed method in this paper can be summarized as follows:

1) A projective transformation method based on camera calibration is proposed. Vehicle position at global coordinate system can be estimated directly. The transformation forms the basis of automatic vehicle classification algorithm as vehicles sizes are unified and no longer related to camera's position and angle.

2) A new classification algorithm is developed to categorize vehicles and non-motorised traffic (pedestrians and bicycles) based on their sizes. Compared to feature -based algorithms, the classification method is more suitable at signalized intersections as vehicle shape is changing for turning vehicles.

3) Several add-on modules are developed to improve existing vehicle detection algorithm. The improved optical flow method is able to detect multiple vehicle types as well as produce continuous vehicle trajectories.

4) Two-dimensional movements and turning path of right-turn and U-turn vehicles are estimated. Speed profiles of vehicles are analyzed and classified into 3 groups. The results can provide sufficient data for building path and speed control schemes of intelligent vehicles.

To apply the proposed method, camera location should be as close to junction-box area as possible to avoid large distortion of vehicle shapes and overlap of vehicles. To overcome this problem, in future studies, multiple cameras can be applied to provide videos in different angles. Through self-calibration, the proposed model can be improved and be more flexible for congested conditions.

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