MVA2005 IAPR Conference on Machine VIsion Applications, May 16-18, 2005 Tsukuba Science City, Japan
10-2

Vehicle Occlusion Identification System by Perceptive Roadway Modeling

Wen-Fong Hu, Yung-Sheng Chen* and Jui-Wei Hsieh
Department of Electrical Engineering, Yuan Ze University, Taiwan, ROC
* eeyschen@ee.yzu.edu.tw
Tel: 886-3-4638800 ext 409

ABSTRACT

This paper presents a vehicle occlusion identification system based on the perceptive characters of a roadway. To tracking the vehicles, two stages are devised, initial parameter setting stage and occlusion handling stage. In the initial stage, a background extracting method is adopted to obtain the first clean background. Then, a road detection algorithm is used for finding the vanishing point. After the lane dividing line detection, the perceptive roadway models are established in each lane. These roadway parameters are fed into the occlusion handling stage for analyzing the vehicle occlusion situations. Due to the different occlusion cases, several novel segmentation methods are proposed for improving the accurate of the tracking vehicles. Experiment results are shown the feasibility of the proposed methods.

Keywords：Occlusion, perceptive, vanishing point, segmentation.

1 INTRODUCTION

Vision-based surveillance system is currently one of the most active research topics due to its powerful capability to extract variety information in comparison with the sensor-based system. Hu et al. [1] indicated the surveillance applications involving people or vehicles including access control in special areas, person-specific identification in certain scenes, crowd flux statistics and congestion analysis, anomaly detection and alarming, and interactive surveillance using multiple cameras. They also addressed the occlusion is one of the major problems in visual surveillance and the possible research directions contain the occlusion handling.

In recent decades, the automated traffic surveillance has become a main stream in the development of Intelligent Transportation System (ITS) that can monitor highways and further analyze the traffic flow and the status of road congestion for traffic management. One main challenging problem in the design of ITS is how to obtain accurate traffic information for tracking the vehicles. However, the key role of a robust tracking system is the occlusion problem. Owing to the occlusion, the error is raising in counting the tracked vehicles during the surveillance period. So, various methods have been proposed for dealing with this problem. Yung et al. [2] presented a vehicle occlusion detection algorithm based on a 3D cuboid model. Gentile et al. [3] proposed a novel segmentation to improve robustness against occlusion in the context of tracking, because homogeneous pieces are more difficult to track than the regions with distinctive properties such as texture or shape. Sanchez [4] analyzed the occlusion phenomena in a video sequence using optical flow estimation. To include providence for partial occlusion of the moving object, Tsechpenakis et al. [5] reformulated one of the most popular deformable templates for shape modeling and object tracking, the Snakes, in a probabilistic manner. Kamijo et al. [6] proposed the Spatio-Temporal Markov Random Field model for segmentation of spatio-temporal images to resolve occlusion problems. Moreover, Veeraraghavan [7] presented a project to monitor activities at traffic intersections for detecting/predicting situations that may lead to accident. The approach contains a low-level image-based blob tracking, an intermediate occlusion-reasoning module, and a mixture of Gaussian models etc. As regards the shadow, Yoneyama et al. [8] proposed a new algorithm to eliminated moving cast shadow for robust vehicle detection and extraction in a vision-based highway monitoring system. But they did not solve the occlusion problem in the paper. Lai et al. [9] presented a visual-based dimension estimation method for vehicle type classification relying on a shadow removal method and an artificial rectangle on the road in advance. Nevertheless, an integrated system is still lack. Koller et al. [10] addressed the problem of occlusion in tracking multiple 3D objects in a known environment and proposed a new approach for tracking vehicles in road traffic scenes using an explicit occlusion reasoning step. But, as shown in Fig. 1, the problem that two occlusive cars enter a frame simultaneously and move together until disappearing in the leaving frame still lack well solution.

In this paper, we proposed a novel vehicle occlusion identification system based on the perceptive characters of the roadway. The diagram, as shown in Fig. 2, depicts the proposed system. The rest of this paper is organized as follows. Section 2 describes the perceptive roadway model based on several algorithms. Section 3 demonstrates the occlusion identification system including vehicle detection, occlusion analysis, and vehicle segmentation etc. Experiment results and conclusion are given in Section 4.

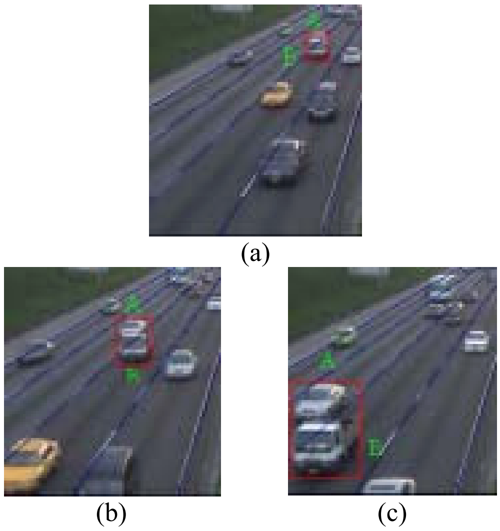


Fig. 1. Three frames in a freeway video. (a)Two cars A and B are occluded when they are entering the lane in the frame #73. (b)The cars A and B are still occluded in the middle frame #83. (c)The cars A and B are still occluded when they are leaving the lane in the frame #93.

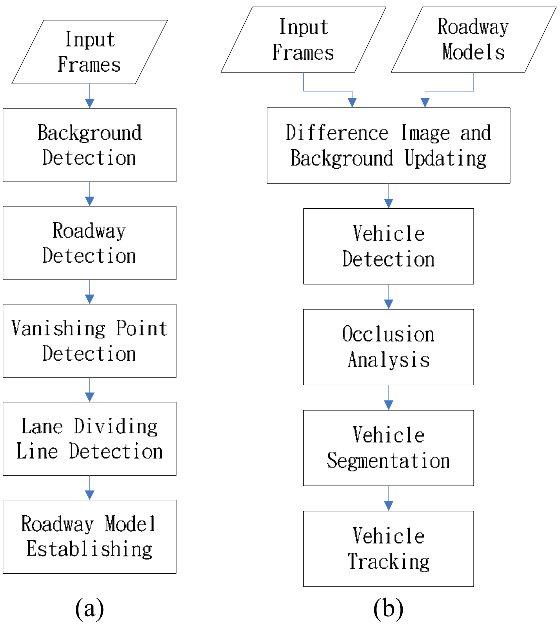


Fig. 2. The diagram of the proposed system. (a)The stage of initial parameter setting. (b)The occlusion handling stage.

2 PERCEPTIVE ROADWAY MODEL

To provide useful information for conquering the occlusion problem, the perceptive roadway should be established in advance. Hence, in this section as shown in Fig. 2(a), a histogram based algorithm is used to extract the initial clean background. And then the roadway detection method we proposed in [11] are adopted to extract the road and further to detect the vanishing point on the road. Based on the trajectory analysis, the lane dividing line can be obtained. Finally, the roadway models for each lane are built using the vanishing point and the dividing lines.

2.1 Background Detection

Due to the histogram of image is a statistical process, its information can be acquired through a large number of images during different time. The peak value of the histogram means the maximum probability of the pixel corresponding to his gray value. The idea is that we try to represent the background by using the gray value of the peak. So, the histogram maximum algorithm is proposed to extract a clean background. But, the algorithm has two mainly shortcomings. One is that to calculate the histogram of every pixel in the image simultaneously needs a grate deal of memory, the other is that just only use the maximum peak value of red, green, and blue bands independently, so the result is affecting by slow motion object drastically. To reduce the memory acquirement the image is partitioned into several sub-images during histogram processing. The problem of slow motion objects can be solved by averaging the N gray value corresponding to the maximum peak and using these peaks' values as the average weightings. The histogram based method we proposed is called histogram maximum average algorithm (HMAA) and adopted to detect the initial background image.

2.2 Roadway Detection

After the obtaining the clean background, the next stage is to extract the lanes on the road built by asphalt. Due to the features of the asphalt road, the rule based method can be used to indicate a pixel on the background is a roadway pixel or not. These rules are described as follows.

- The saturation of the pixel is large than 0 and less than 1.
- The absolute value of the ratio of R to G band is less than the average of RG ratio.
- The absolute value of the ratio of R to B band is less than the average of RB ratio.
- The absolute value of the pixel intensity is less than the average intensity.
- The absolute value of color purity of the pixel is less the average color purity.

The results of roadway detection as demonstrated in Fig. 3.

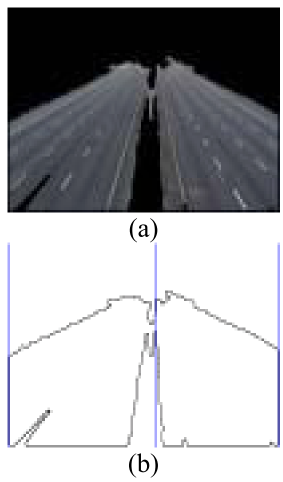


Fig. 3. The results of roadway detection in a free way. (a)The extract roadway. (b)The right and left lanes can be separated using vertical histogram based algorithm.

2.3 Vanishing Point Detection

Because the lanes are detected in the previous stage, the boundaries can obtain easily using morphology operations. To extract two lines on the both side of a lane from its boundary map, the boundary analysis is needed. First, the boundary map is passed through a thinning operation for ensuring the line width is one pixel. Second, these boundaries points are recorded in an array and the directions for each two adjacent points are made. Therefore, based on the information of directions and the locations of boundary points, the boundary lines can be gained through the line fitting algorithm. The boundary lines of left and right lanes with red color are shown in Fig. 4 and the intersection point of the lines is the vanishing point of the roadway.

Fig. 4. The vanishing point and the boundary lines of the left and right lanes.

2.4 Lane Dividing Line Detection

Due to the most of vehicle drivers obey the traffic rules, the trajectories of vehicle are useful for detecting the dividing lines of a lane on condition that a few abnormal trajectories are removed in advance. In the initial stage, a rough tracking without dealing with the occlusion problem is adopted and the trajectories of the tracked vehicles are recorded in arrays. Therefore, the slopes of each two adjacent points can be calculated using the simple formula $m = \Delta y / \Delta x$, where m is the slope, Δy the difference of vertical coordinate, and Δx the difference of horizontal coordinate. To obtain the dividing line, the useless trajectories data should be given up if they satisfy one of the following conditions.

- The two values of adjacent slope of a vehicle change abruptly.
- The main slope of a vehicle is beyond the range of left and right boundary slope.

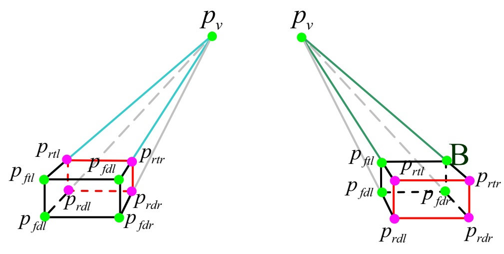
According to the well trajectories of vehicles, the average locations of vehicle trajectories of each lane can be obtained. Furthermore, the vanishing point is found in the previous session, so the virtual trajectory lines of vehicles can be made by using the line fitting algorithm starting from the vanishing point. Finally, the dividing lines of the lane can be acquired easily by averaging the adjacent virtual trajectory lines. Fig. 5 exhibits the lane dividing lines on a freeway using red color.

(a) (b)

Fig. 5. The dividing lines on a freeway. (a)The left roadway. (b)The right roadway.

2.5 Roadway Model Establishing

The diagram of perceptive roadway models is depicted in Fig. 6 including both left and right roadway models. The eight points on the downside represent the vertexes of a 3D vehicle.



(a) (b)

Fig. 6. The diagram of perceptive roadway models. (a)The left roadway model. (b)The right roadway model.

The black rectangle plane consisted of p_{ftl}, p_{ftr}, p_{fdr}, and p_{fdl} represents the front side of a vehicle and the red rectangle plane consisted of p_{rtl}, p_{rtr}, p_{rdr}, and p_{rdl} stands for the rear side of the vehicle. The points p_{rdl} and p_{rdr} on the each of right lane and the points p_{fdl} and p_{fdr} on the each of left lane can be obtained by finding every intersection point of the boundary lines and the lane dividing lines gained in the previous sessions. For the sake of expressing the concept of multiple lane models, we just used a square box to represent the front or rear side of vehicle. Therefore, according to the simple geometry property of a square i.e. the length of each side is the same, either the points p_{ftl} and p_{ftr} on the left lanes or p_{rtl} and p_{rtr} on the right lanes can be calculated. The results are demonstrated in Fig. 7. Moreover, observing the established model, we found that the rectangles are changing their size gradually in spite of vehicle is moving near to or leaving away from the P_v. An idea is rose that if we can predict the size of a vehicle when it is passing through a roadway model, the occlusion problem should be resolve. Due to the different views of the lanes, we must establish the parameters for every lane by tracking the vehicles in their individual ways. Fig. 8 demonstrated a vehicle moves forward to the vanishing point on a lane. The horizontal lines named as $t_0, t_1, \ldots$ are the standard time units obtained by tracking vehicles with uniform motion. For example, $t_3 = 3$ means a standard vehicle moving three unit times starting from $t_0 = 0$. The three points p_0, p_1, and p_2 are the intersection points of the left boundary line and horizontal lines t_0, t_1, and t_2, respectively. The trapezoids filled with brown and green colors represent the starting (p_A, p_B) and ending ($p_{A'}, p_{B'}$) position of a vehicle. The p_A and p_B are the front and rear position of the vehicle at the starting position. The $p_{A'}$ and $p_{B'}$ are the front and rear position of the vehicle at the ending position. The horizontal lines t_{ET}, t_{ED}, t_{ST}, and t_{SD} are the time when the vehicle arrived the positions $p_{A'}$, $p_{B'}$, p_A, and p_B. The distance symbol d_{01} is the distance from t_0 to t_1, d_{12} from t_1 to t_2, d_{ST} from t_0 to t_{ST}, d_{SD} from t_0 to t_{SD}, d_{ET} from t_1 to t_{ET}, and d_{ED} from t_1 to t_{ED}, respectively.

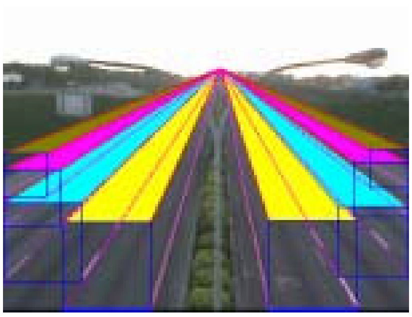


Fig. 7. The roadway models on a free way.

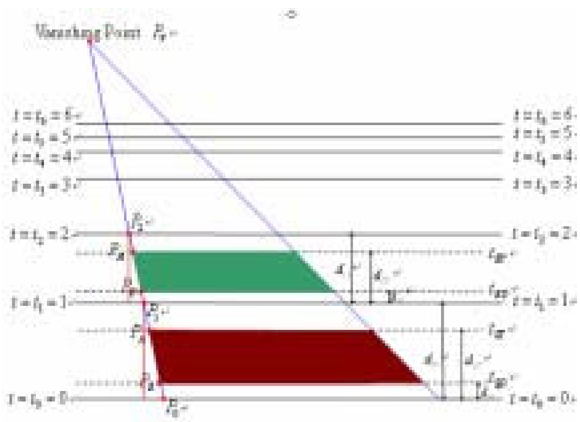


Fig. 8. A vehicle moves forward to the vanishing point on a lane only using the bottom of the proposed roadway model. The trapezoids filled with brown and green colors represent the starting and ending position of a vehicle, respectively.

3 OCCLUSION HANDLING

After established the roadway models, the next step is to deal with the occlusion problem using the obtained information for improving the robustness of a tracking system. Due to the different situations of occlusion, the process of occlusion analysis is needed and then the relative strategies for segmentation are also demanded. They are discussed in the following subsections.

3.1 Occlusion Analysis

Due to the view angle of an observer, the moving objects may be occluded by each other. Fig. 9 demonstrates a un-occlusion case and five occlusion cases. To identify the different cases of occlusion, in this paper, three occlusion analysis methods are proposed including vehicle size analysis, crossing roadway analysis, and block abnormal analysis. First, based on the perceptive roadway models built in the initial stage, the maximum size of a vehicle on arbitrary position of a lane has been known in advance. Therefore, if two vehicles are occluded by each other, the bounding box size will become too large and it can be found easily. Although the vehicle occlusion is identified by the perceptive roadway models, the different kinds of occlusion cases are still unknown for adopting the corresponding segmentation strategies to deal with them. Thus, the crossing roadway analysis method is developed to detect whether a bounding box is across the corresponding lane dividing line or not. The method is implemented without difficulty by testing every point of the bounding box is also a point of the lane dividing lines.

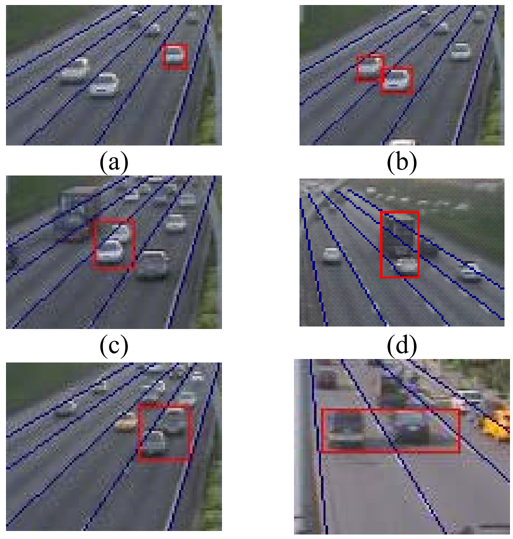
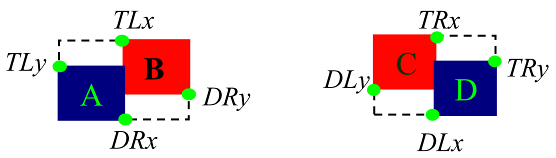


Fig. 9. (a)The un-occlusion case of a single car. (b)The occlusion case of crossing a roadway. (c)The first kind of front-rear occlusion case. (d)The second kind of front-rear occlusion case. (e)The third kind of front-rear occlusion case. (f)The occlusion case caused by shadows.

Moreover, by observing the Fig. 9 (b) and (e), the cars are occluded in left-right direction and we called this case is left-right occlusion case as shown in Fig. 10. Because the important features of this case are the four block region with white color, in this paper, the block abnormal analysis is proposed to identify it. The algorithm is described as follows and some variables used in the algorithm as depicted in Fig. 10.



(a) (b)

Fig. 10. Two left-right occlusion cases. A, B, C, and D represent four vehicles.

The algorithm of block abnormal analysis:

Step 1: Scan the first row of a bounding box from top-left point in the horizontal direction to find the first pixel with nonwhite color and record the x coordination of the pixel as TL_x.

Step 2: Scan the first column of the top-left corner from top-left point in the vertical direction to find the first pixel with nonwhite color and record the y coordination of the pixel as TLy.

Step 3: Calculate the area $nBoxarea$ of the region made by TLx and TLy.

Step 4: Calculate the density $dDensity$ of the region using the formula of $dDensity = \frac{object\ \ pixels\ in\ nBoxarea}{nBoxarea}$.

Step 5: Scan every row of the region and record the maximum values with continues white color, individually. Then, find the maximum value $nHMax$.

Step 6: Scan every column of the region and record the maximum values with continues white color, individually. Then, find the maximum value $nVMax$.

Step 7: The corner is recorded as a candidate of left-right occlusion if the value of $dDensity$, $nHMax$, and $nVMax$ exceed the predefined thresholds.

Step 8: Repeat Step 1 to 7 by using the top-right, down-right, and down-left corners and find the candidates of left-right occlusion respectively.

Step 9: If the numbers of the candidates are more than two, this bounding box is identified as left-right occlusion.

3.2 Vehicle Segmentation

After the occlusion analysis, the next stage is to segment the bounding box of occlusion caused by different cases. As show in Table 1, the vehicle occlusion happened if the area of detected bounding box is too large by using the perceptive roadway models. Second, if the abnormal block analysis is true, the segmentation strategy we adopted is block method. Otherwise, the segmentation strategy is used depending on whether the crossing roadway analysis is valid or not. If the analysis is true, the virtual roadway method is adopted, otherwise the edge based method is used. Due to the effect of the vehicle shadows as depicted in Fig. 9(f), the Gaussian mode is introduced to reduce the occlusion situation. The four segmentation strategies are described in following sub-sessions.

Occlusion / Situations	case 1	case 2	case 3	case 4
vehicle area too large	Yes	Yes	Yes	Yes
vehicle crossing a roadway	Yes	-	No	Yes
abnormal block	No	Yes	No	-
containing shadows	No	No	No	Yes
segmentation strategy	virtual roadway method	block method	edge method	Gaussian method

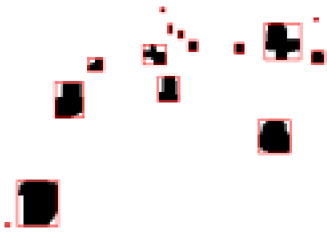
Table 1. Four occlusion cases and relative segmentation strategy. The symbol "–" represent that the case without do the relative analysis method.

The purpose of dealing the occlusion problem is to promote the tracking result, so the edge method is work well although it just got rough segmentation result. Moreover, due to the roadway models and car models are built in the stage of initial parameter setting, we can predict the 3D bounding box of a car and do the further analysis.

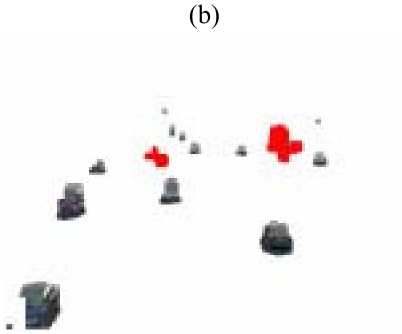
4 RESULTS AND CONCLUSION

In this paper, two stages are devised to identify the occlusion cases for tracking vehicles including initial parameter setting stage and occlusion handling stage. In the initial stage, the background extracting method, road detection algorithm, lane dividing line algorithm are designed to obtain the perceptive roadway models. And then these roadway parameters are fed into the occlusion handling stage for analyzing the vehicle occlusion situations. Due to the different occlusion cases, several novel segmentation methods are proposed for improving the accurate of the tracking vehicles. The results are shown in Fig. 13 including source image, moving objects detection, occlusion object detection, and segmentation result. Experiment results are shown the feasibility of the proposed methods.

(a)



(b)



(c)

(d)

Fig. 13. The results of the proposed system. (a)Source image. (b)Moving objects. (c)Occlusion objects. (d)Segmentation Results.

Acknowledgments:

This work was supported partially by National Science Council of Republic of China under Grant NSC92-2213-E-155-052.

REFERENCE

[1] W. Hu, T. Tan, L. Wang, and S. Maybank, “A survey on visual surveillance of object motion and behaviors,” *IEEE Tran. On Systems, Man and Cybernetics*, vol. 34, no. 3, pp. 334-352, 2004.

[2] N.H.C. Yung and A.H.S. Lai, “Detection of vehicle occlusion using a generalized deformable model,” *Proceedings of IEEE International Symposium*, vol. 4, pp.154-147, 1998.

[3] C. Gentile, O. Camps, and M. Sznaier, “Segmentation for robust tracking in the presence of severo occlusion,” *IEEE Trans. Image Processing,* vol. 13, no. 2, pp. 166-178, 2004.

[4] O. Sanchez, “Tracking of an occluded object in a video sequence,” *Proceedings of Signal Processing and Its Applications,* vol. 2, pp. 231-234, 2003.

[5] G. Tsechpenakis, K. Rapatzikos, N. Tsapatsoulis, and S. Kollias, “Object tracking in clutter and partial occlusion through rule-driven utilization of snakes,” *International Conference on Multimedia and Expo*, vol. 3, pp. 69-72, 2003.

[6] S. Kamijo and M. Sakauchi, “Segmentation of vehicles and pedestrians in traffic scene by spatio-temporal markov random field model,” *International Conference on Multimedia and Expo*, vol. 2, pp. 285-288, 2003.

[7] H. Veeraraghavan, O. Masoud, and N.P. Papanikolopoulos, “Computer vision algorithms for intersection monitoring,” *IEEE Trans. Intelligent Transportation Systems,* vol. 4, no.2, pp.79-89, 2003.

[8] A. Yoneyama, C.H. Yeh, and C.-C.J. Kuo, “Moving cast shadow elimination for robust vehicle extraction based on 2D joint vehicle/shadow models,” *Proceedings. IEEE Conference on Advanced Video and Signal Based Surveillance,* pp. 229-236, 2003.

[9] A.H.S. Lai, G.S.K. Fung, and N.H.C. Yung, “Vehicle type classification from visual-based dimension estimation,” *Proceedings. IEEE Intelligent Transportation Systems,* pp. 201-206, 2001.

[10] D. Koller, J. Weber, and J. Malik, “Robust multiple car tracking with occlusion reasoning,” *in Proceedings. Eur. Conference on Computer Vision*, vol. 1, pp. 189-196, 1994.

[11] W.F. Hu, Y.S. Chen, and J.W. Hsieh, “A lane extraction algorithm for a province video sequence,” *Journal of Ching-Yun University*, vol. 24, no. 1, pp. 61-66, 2004.