International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:2, No:12, 2008

Moving Vehicles Detection using Automatic Background Extraction

Saad M. Al-Garni, and Adel A. Abdennour

***Abstract*—**Vehicle detection is the critical step for highway monitoring. In this paper we propose background subtraction and edge detection technique for vehicle detection. This technique uses the advantages of both approaches. The practical applications approved the effectiveness of this method. This method consists of two procedures: First, automatic background extraction procedure, in which the background is extracted automatically from the successive frames; Second vehicles detection procedure, which depend on edge detection and background subtraction. Experimental results show the effective application of this algorithm. Vehicles detection rate was higher than 91%.

***Keywords*—**Image processing; Automatic background extraction; Moving vehicle detection.

I. Introduction

VEHICLE detection is very important for civilian and military applications, such as highway monitoring, and the urban traffic planning. For the traffic management, vehicles detection is the critical step. Vehicles detection must be implemented at different environment where the light and the traffic status changing. Vehicles detection could be achieved using the common magnetic loop detectors which are still used even though they are not the effective. Loop detectors are considered as point detectors and could not give the traffic information for the highway. Vision based techniques are more suitable than the magnetic loop sensors. They do not disturb traffic while installed and they are easy to modify. Their applicability is more comprehensive because they could be used in many aspects as vehicle detection, counting, classification, tracking, and monitoring. One camera could be used to monitor large section of highway. In spite the apparent advantages of vision based methods there are still many challenges. These challenges are weather changes, sun light direction and intensity changes, building shadows, vehicles have different sizes, shapes and colors.

In this paper one digital camera installed over the freeway to detect successive images. Detected images could be analyzed to extract the background automatically. Each image contains background of the highway and the moving vehicles. It is difficult to get freeway image without moving vehicles (background), so the freeway background must be extracted from the sequence images. The extracted background is used in subsequent analysis to detect moving vehicles.

This paper presents the related work in the next section. In section three, the proposed method for background extraction procedure is presented in detail. Vehicles detection procedure is proposed in section four. Finally the application of the proposed technique is given in section five and the conclusions are drawn in section six.

S. M. Al-Garni is with the Electrical Engineering Department , King Saud University, College of Engineering, Riyadh, Saudi Arabia, P. O. Box 800, Riyadh 11421 (e-mail: algarnis2@yahoo.com).

A. A. Abdennour is with the Electrical Engineering Department , King Saud University, College of Engineering, Riyadh, Saudi Arabia, P. O. Box 800, Riyadh 11421 (phone: 96614676752; fax: 96614676757; e-mail: adnnour@ksu.edu.sa).

II. Related Work

Current approaches for vehicles detection try to overcome the environment changes. Some approaches achieve the detection using background subtraction only and predicting the background through the next update interval [1]. In these approaches the background is not extracted but detected and then updated through the next images processing. Intensity changes, stopped vehicles (or very slow moving vehicles) and camera moving lead to miss detection in these techniques. It is used to detect vehicle in simple scenes.

Another approach uses edge-based techniques [2]. In this approach 3D model is proposed for the vehicle. This 3D model depends on the edge detection of the vehicle. It is applicable under perfect conditions for passenger vehicles only. The edge in image processing is abrupt change in the intensity values. The edge detection suffers from many difficulties such as vehicle shadows, dark colors and ambient lights. Edge detection process becomes more difficult when vehicle color is close to the freeway color.

In other approaches such as probabilistic and statistical methods [3, 4, 5], there is not strict distribution for vehicle model so they use the better approximations for the unknown distributions, this leads to intensive computations and time consuming. The results of applied these methods will lead to high miss detection, and could not apply for complicated scenes. In these techniques, detection rate is low as compared to the other approaches.

Other approaches use explicit detail model [6, 7], where they need detail model and a hierarchy for detail levels. In [6] the model contains substructures like windshield, roof, hood, and radiometric features as color constancy between hood color and roof color (where the gray level is higher than the median of the histogram). It is apparent that a large number of models are needed to cover all types of vehicles. In [7] a hierarchical model is used to decide on the detection step (that identifies and clusters the image pixels) which pixels have a strong probability to belong to vehicles. In this case a huge computation is needed to detect the vehicles, and this will result in miss detection for different shapes of vehicles.

In [8] vehicle detection is implemented by calculating various characteristics features in the image of a monochrome camera. The detection process uses shadow and symmetry features of vehicle to generate vehicle hypothesis. This is beneficial for driver assistance but it is not applicable for vehicles counting and complicated scenes.

In [9, 10] neural networks were used for vehicle detections. Neural networks have drawbacks; the main one is that there is not warranty that they reach the global minimum (in this case there are not closed-form solutions for modeling the vehicle detection). The other one implies to learn a data set representative of the real world and there is not universal optimum model for neural network.

In [11] fuzzy measures are used to detect vehicles. The detection process depends on the light intensity value. When light intensity value falls in certain interval, fuzzy measures must be used to decide if it is a vehicle or not. When the intensity value is larger than this interval, it represents a vehicle and when it is less than this interval vehicle does not exist. This approach suffers from environment light changes and interval determination that needed to apply the fuzzy measures.

In this paper, background extraction and edge detection is used to detect vehicles. This is useful in two ways, the first is using the advantages of the background subtraction and edge detection to detect vehicles. Second one it is able to deal with complex scenes and treat the intensity changing problems.

III. Automatic Background Extraction

To extract the freeway background automatically enough number of successive frames must be available for processing. The automatic background extraction starts by processing the first three successive frames (images) as in the following steps [10]:

Step1. Take a movie for the freeway and then convert it to number of successive frames (images).
Step2. Use the first three successive frames C^{t-2}, C^{t-1}, C^{t} to calculate the differences
$D^{t-1,t-2} = |C^{t-1} - C^{t-2}|$, and $D^{t,t-1} = |C^{t} - C^{t-1}|$.
Step3. Specify the gray threshold level T.
Step4. Convert the differences to binary depend on the threshold.
Step5. Calculate the Difference Product (DP) using the bitwise logical AND operation:
$DP^{t} = DB^{t-1,t-2}\ \&\ DB^{t,t-1}$.
Step6. Apply binary dilation (DLT) of DPti,j .
Step7. Apply image close.
Step8. Calculate moving object region (MOR) by filtering the closed image.
Step9. Fill the moving object region.
Step10. Estimate the initial background B(kk) and store this region information at the EF (Extraction Flag).
B(kk) = MOR(kk)|C^{t}, where the symbol '|' is the bitwise logical OR operator.
And, EF(kk) = MOR(kk).
Step11. For the first three successive frames calculate MOR for current input image and calculate background extraction target area (ETA).
ETA(kk) = EF(kk-1)& $\overline{MOR}(kk)$, where $\overline{MOR}(kk)$ = 1's complement of MOR(kk).

Step12. For the subsequent frames extract background pixels in the current input image and update EF.
B(kk) = B(kk-1) & (C^{t}| $\overline{ETA}(kk)$),
EF(kk) = EF(kk-1) $\oplus$ ETA(kk) , where $\oplus$ is the bitwise logical XOR (exclusive XOR) operator.

Repeat steps 1-12 till get the background.

Fig. 1 summarizes the steps of this process.

IV. Vehicles Detection

To detect vehicles the extracted background must be subtracted from the current image as in the following steps:

Step1. Subtract the extracted background from the current image.
Step2. Find the edge of the current image and the background image.
Step3. Subtract the edge of the background image from the edge of the current image.
Step4. Fill the resulted images in steps 2&3. Implement logical And operation for the results in steps 2&3.
Step5. Filter the resulted image.
Step6. Count the resulted moving vehicles.

Fig. 2 summarizes the steps of this process.

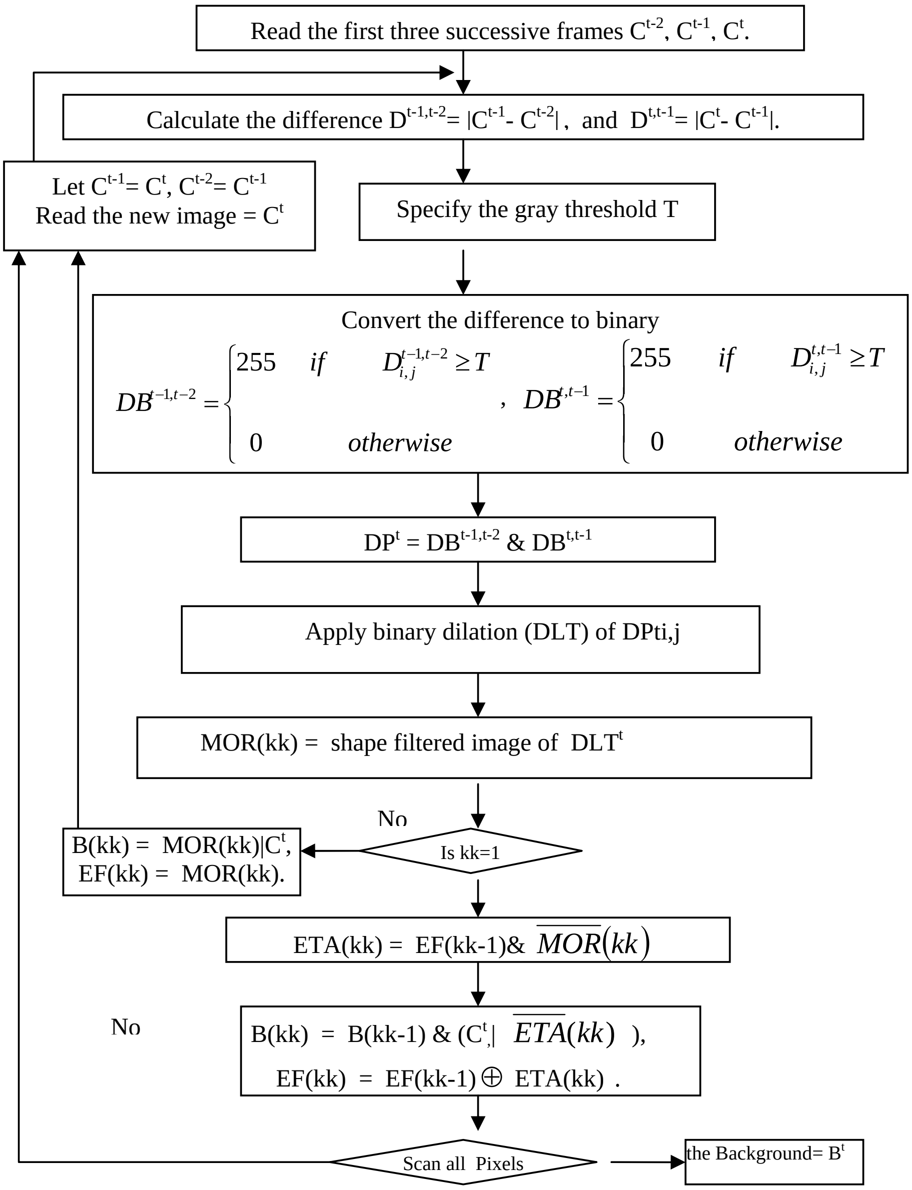

Fig. 1 Flow chart for Automatic Background extraction

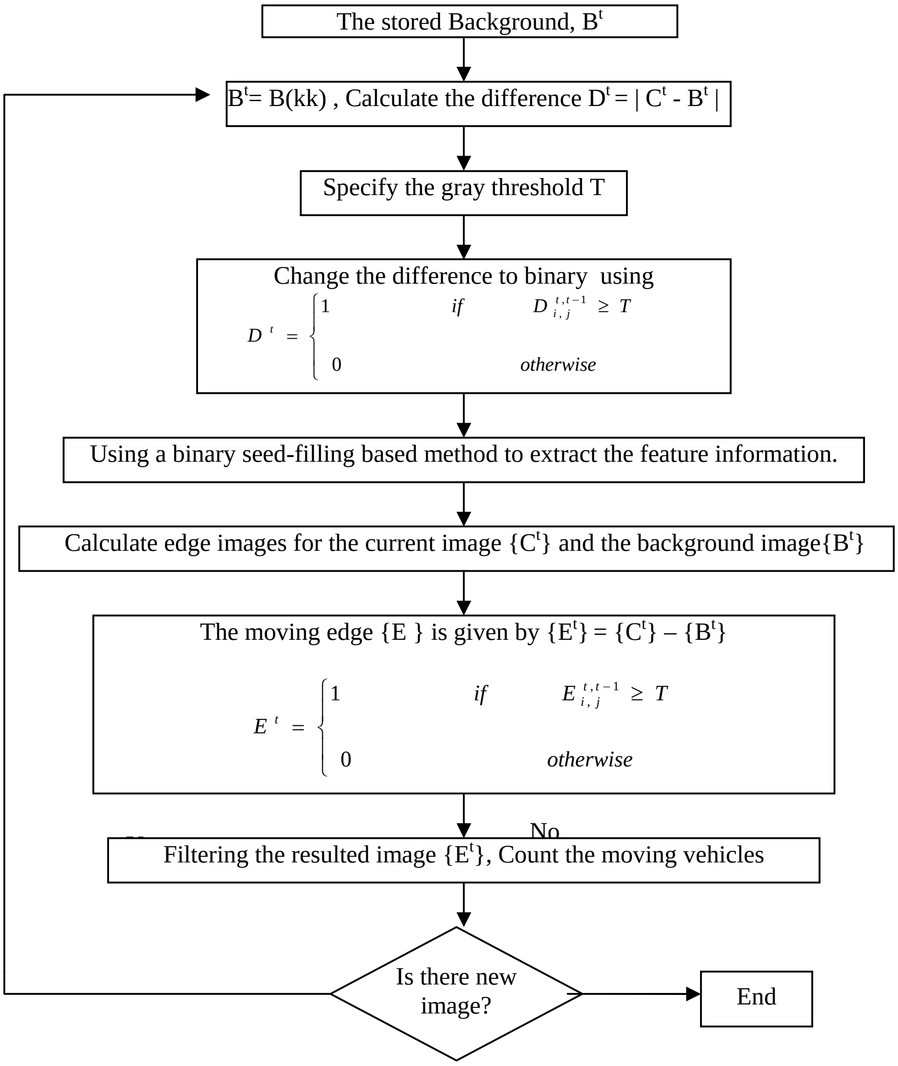

Fig. 2 Flow chart for vehicles detection based on background extraction

V. RESULTS

A. Automatic Background Extraction

Freeways are originally designed to provide high mobility to road users. However, the increase in vehicle numbers has lead to congestion forming in freeways around the world. Daily recurrent congestion substantially reduces the freeway capacity when it is most needed. Expanding existing freeways cannot provide a complete solution to the congestion problem due to economic and space constraints. Automatic monitoring for the freeways is the efficient method to use the existing freeways efficiently. Its implementation need to detect vehicles using automatic background extraction. Background extraction is the main step for vehicle detection. Fig. 3 shows number of successive frames that are used to extract the background. Digital camera used to take shots. The camera placed over the highway directly. It shots six frames per second. The images are taken midday to decrease the effect of the vehicle shadow problems.

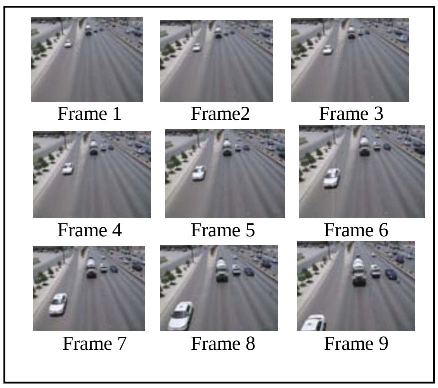

Fig. 3 Number of successive frames that are used for background detection

Fig. 4 gives the results of the proposed technique for background extraction.

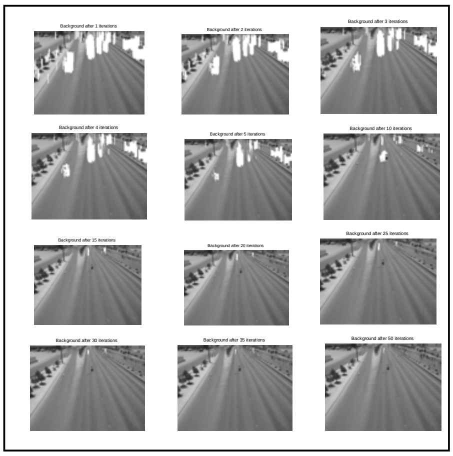

Fig. 4 Automatic Background extraction results

The automatic background extraction results are very good and promising. The most effective parameters that are playing a main role for automatic background extraction are the threshold level and the dilation. The threshold value is specified using Otsu threshold. This threshold is used for segmentation to extract the moving vehicles from the background. Matlab has a built-in function that evaluates the Otsu threshold. The dilation used in this approach is line with angle 90° because the camera has an angle of 90° with respect to highway.

B. *Vehicles Detection*

Table I gives vehicle detection results. The background is subtracted from the current image then the resulted image is filtered to get moving vehicles only. By using this technique most of vehicles are detected. Moving vehicles are detected easily after background is subtracted.

TABLE I
THE RESULTS FOR VEHICLE DETECTION ARE SHOWN

Case number	Actual Number of vehicles	Detected Vehicles	Rate%
1	13	12	92
2	12	11	91
3	10	10	92
4	13	12	92
5	11	10	91
6	14	13	92
7	13	12	91
8	12	11	91

VI. CONCLUSION AND FUTURE WORK

The experimental results of applying this approach lead to detect moving vehicles efficiently. This approach gives promising and effective results where vehicle detection rate was higher than 91%. In this approach the advantages of background subtraction and edge detection are used. It is could be improved and used as a basis for automatic freeway traffic monitoring. Miss detection resulted from occluding big vehicles the small ones and the far moving vehicles that appear as a point in the image. These difficulties could be solved in the future work by install the camera over a high building near the highway and take shots for the cross section of the highway.

REFERENCES

[1] S. Gupte, O. Masoud, R. Martin, and N. Papanikolopoulos, “Detection and classification of vehicles,” IEEE Trans. Intelligent Transportation Systems, vol. 3, no. 1, March 2002, pp. 37 – 47.
[2] Z. Kim and J. Malik,; “Fast vehicle detection with probabilistic feature grouping and its application to vehicle tracking”,. Ninth IEEE International Conference on Computer Vision, 13-16 Oct. 2003, pp. 524 – 531.
[3] H. Schneiderman, and T. Kanade, “A statistical method for 3D object detection applied to faces and cars,” IEEE Conf. Computer Vision and Pattern Recognition, vol.1, 13-15 June 2000, pp. 746 - 751.
[4] T. Zhao, and R. Nevatia, “Car detection in low resolution aerial image,” Image and Vision Computing, vol. 21, 18 march 2003, pp. 693 – 703.
[5] A. Rajagopalan, P. Burlina, and R. Chellappa, “Higher order statistical learning for vehicle detection in images,” in Proc. 7th Int. IEEE Conf. Computer Vision, vol. 2, 20-27 Sept. 1999, pp. 1204 -1209.
[6] S. Hinz, “Detection and counting of cars in aerial images,” in Proc. Int. Conf. Image Processing, vol. 3, 14-17 Sept. 2003, pp. 997-1000.
[7] R. Ruskone, L. Guigues, S. Airault, and O. Jamet, “Vehicle detection on aerial images: a structural approach,” in Proc. 13th Int. IEEE Conf. Pattern Recognition, vol. 3, 25-29 Aug. 1996, pp. 900 - 904.
[8] C. Hoffman, T. Dang, and C. Stiller, “Vehicle detection fusing 2D visual features,” in Proc. IEEE Intelligent Vehicles Symposium, 14-17 June 2004, pp. 280 – 285.
[9] S. Mantri, and D. Bullock,“A neural network based vehicle detection and tracking system,” in Proc. 27th Southeastern Symposium on System Theory, 12-14 March 1995, pp. 279 – 283.
[10] D. Ha, J. Lee, and Y. Kim, “Neural-edge-based vehicle detection and traffic parameter extraction,” Image and vision computing, vol. 22, 2004, pp. 899-907.
[11] Z. Liu, X. Li, and X. Leung, “Fuzzy measures for vehicle detection,” The 10th IEEE Int. Conf. Fuzzy Systems, vol. 2, 2-5 Dec. 2001, pp. 848 – 851.