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Fast Vehicle Detection and Counting Using Background Subtraction Technique and Prewitt Edge Detection

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***Abstract*– Fast vehicle detection is an important task for the purpose of detecting, counting and tracking the vehicles on the highways. In our method, we propose a new, fast way to identify the vehicles on the highways based on the image processing techniques, such as background subtraction, Prewitt filter and various morphological operations. First, we used adaptive background subtraction technique to extract the moving objects of the current frame, next we used morphological operations to remove the unrelated objects to the vehicles. Experimental results show the high accuracy of the proposed method along with low time complexity.**

***Index Terms*– Background Subtraction, Automatic Vehicle Detection, Prewitt Filter and Thresholding**

I. INTRODUCTION

TRAFFIC management due to increased traffic on the roads, is an important part of the daily routine. Automatic vehicle detection in traffic scenes and information extracted from the vehicles can lead to better traffic management in busy highways. Monitoring and measuring the traffic flow can be achieved through sensors [1], [2] as well as through image processing techniques.

Monitoring traffic using image processing techniques, has led us to measure parameters such as the flow of traffic, vehicle speed, number of vehicles, etc. Image processing is used in traffic surveillance for vehicle tracking, recognizing license plates, identifying obstacles in the road, etc. Traffic surveillance with image processing can lead to better controlling of traffic flow and detection of indiscreet drivers and illegal speed offenders. In the past, many researchers provided various ways to automatically detect vehicles using image processing techniques. This project aims to test the effectiveness of our proposed method designed to detect and track the vehicles at the inspection videos.

Our proposed method uses the adaptive background subtraction technique, followed by morphological operations to locate and detect vehicles and to remove irrelevant objects. The proposed method is computationally cost-effective. This paper will explain, review and test the proposed system and includes the performance test and conclusion.

The remainder of the paper is organized as follows: in Section II, a survey of vehicle detection methods is presented. In Section III the proposed method for vehicle detection is introduced. In Section IV, the experimental results of the proposed method have been shown, and Section V, finalizes our conclusions and future work.

II. SURVEY OF VEHICLE DETECTION METHODS

In [3], [4], methods are based on probability and statistics, however since no certain distribution for modeling the vehicles exist, they used a better approximation to describe the unknown distribution, however this methods are time-consuming and requires extreme computation.

In [5] vehicle detection uses different characteristics which measured through monochrome camera. The process of recognition uses the information of shadows and symmetrical features of the vehicle to detect possible vehicles. This is to help the driver but it is unsuitable to detect the number of vehicles.

In [6], [7] neural networks were used to detect vehicles. Neural networks have flaws, the biggest disadvantage is that finding the global minimum is not guaranteed (in vehicle detection there is no close way to modeling for identifying the vehicles). Another problem is that neural networks should be trained using real-world data, but there is no global optimum for neural networks in the case of vehicles.

[8] Also uses the background subtraction and then, the vehicles tracked based on contour extraction. It uses Prewitt filter for edge detection. The contour linking method used for connecting sparse edges together and to create one closed contour. This method, which may include video inspection of objects other than the vehicles, there will be high rate of misdetection, Due to difficulty of removing irrelevant objects.

III. THE PROPOSED METHOD

In this section, we propose a method to detect the vehicles in the scene based on the two steps. First step is the noise removal using the median filter, next we detect the edges in both the current frame and the background model, next we use the adaptive background subtraction technique so that we can remove the irrelevant objects from the current frame, Afterwards, in the second step we use morphological operations and thresholding to detect vehicles and remove the other objects and noises on the scene

A) Preparing the Frame to Locate Vehicles

In this section, first, we use a median mask to reduce the noise in the current frame and the background model (the average total of 10 frames before the current frame), next Prewitt edge detection is performed, next using adaptive background subtraction, current frame subtracts background model, so that we can use morphological operations to detect vehicles. Before using edge detection methods, we used a 4×3 median mask for noise elimination. This filter applies to both current frame and the background model.

1) Edge Detection

Edge detection is the process of identifying and locating sharp discontinuities in the intensity of pixels which belongs to object boundaries [9]. There are many ways to perform edge detection including: Laplacian, Roberts, Sobel, Canny. Between this methods. Between this methods, we used Prewitt filter due to its speed and simplicity and the thin detected edges (after background subtraction), for our proposed method. The Prewitt operator consists of a pair of 3×3 convolution masks as shown in Eq. (1) and Eq. (2).:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \tag{1}$$

$$G_y = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} \tag{2}$$

Fig. 1 shows one of the frames used for edge detection, and Fig. 2 shows the result of edge detection of Fig. 1.

2) Threshold Technique

At this point, a threshold is selected for Roberts filter. The key parameter in thresholding is selecting the correct threshold. Coders can manually select a value or can let an algorithm select the proper threshold, which is known as automatic thresholding [10]. Here we have determined the value of threshold manually, by trial and error. The threshold image in general is defined according to Eq. (3):

$$g(x,y) = \begin{cases} 1, & if\ f(x,y) \geq T \\ 0, & if\ f(x,y) < T \end{cases} \tag{3}$$

3) Adaptive Background Subtraction

Adaptive background subtraction is one of the techniques in the field of image processing and machine vision. It extracts the information of objects from current frame, by subtracting the current frame from the background model. After the image pre-processing step (which includes noise removal, etc.), adaptive background subtraction can be used to determine the area of moving objects. The background subtraction technique is used extensively for detection of moving objects in fixed cameras, we can detect the movement of objects by calculating the difference between the current frame and the average total of several previous frames, known as “background frame” or “background model”. Background model usually is the average total of N previous frames. Here we consider N equal to 10. The resulted image from background subtraction shown in Fig. 3.

Fig. 1: Sample Frame Used For Edge Detection

Fig. 2: Result of Prewitt Edge Detection Method

Fig. 3: Image before Object Detection

4) Removing Weak Sparse Edges

At this point first we convert the Fig. 3 Image to double precision space. Then we use a 2-by-2 median filter to calculate the power of neighborhood edges. If neighborhood edges are strong, then the result of the calculation will be a large value, hence we set $g(x, y)$ to one. For this purpose we put a threshold on the mask. We determined the value of threshold manually, by trial and error. The calculation is according to Eq. (4),

As a result, we remove some of the sparse edges on the scene.

$$g(x,y) = \begin{cases} 1, & if\ median_{2\times2}(x,y) \geq T \\ 0, & if\ median_{2\times2}(x,y) < T \end{cases} \qquad (4)$$

B) Detection of Vehicle Locations

First, we used the morphological operations to connect close pixels together and to remove irrelevant edges, so we can indicate the location of vehicles, and finally the resulted image is the possible location of the vehicles which we mark them by finding their correspondent centroid.

1) Object Detection

Fig. 4 shows the flowchart for vehicle counting.

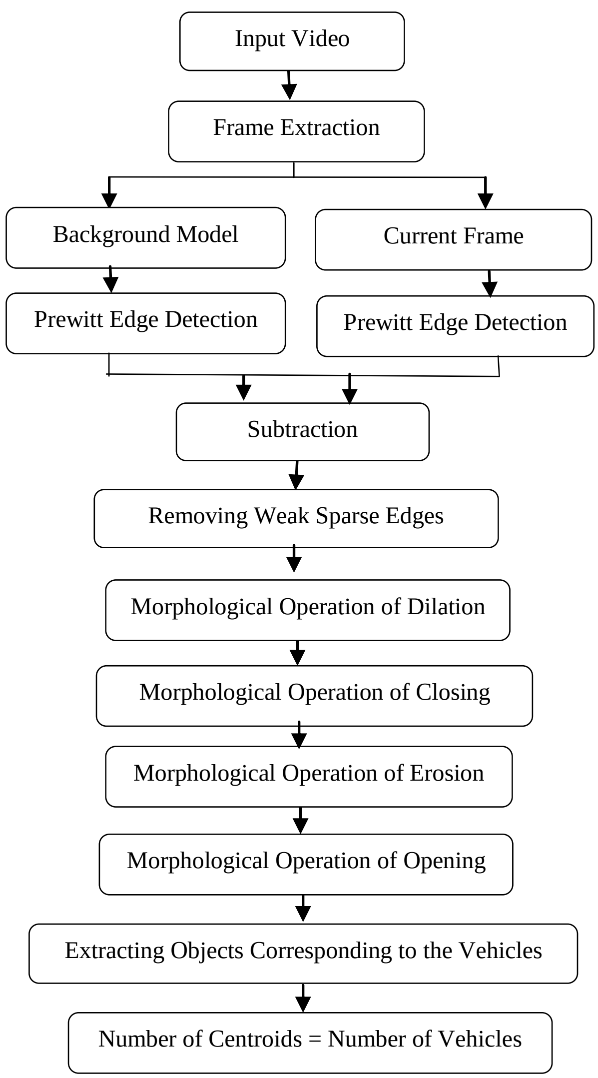

Fig. 4: Flowchart for Vehicle Detection and Counting

In this section, morphological operations are used for matching patterns related to the vehicles. Output image includes the only edges related to the vehicles. By using morphological operation first we dilate the remained pixels with 5×5 square structural element and then we fill the holes between closed contours with morphological operations. The dilation of $A\ by\ B$ is defined by Eq. (5). In this way we can fill the void of incorporate pixels of the vehicles. Next, use 3×3 square structural element of morphological closing operation on the image. Morphological closing is defined according to Eq. (6).

$$D(A,B) = A \oplus B = \bigcup_{b\in B} A_b \qquad (5)$$

$$A \cdot B = (A \oplus B) \ominus B \qquad (6)$$

In Eq. 6, $\oplus$ and $\ominus$ denote dilation and erosion, respectively. The resulted image is shown in Fig. 5.

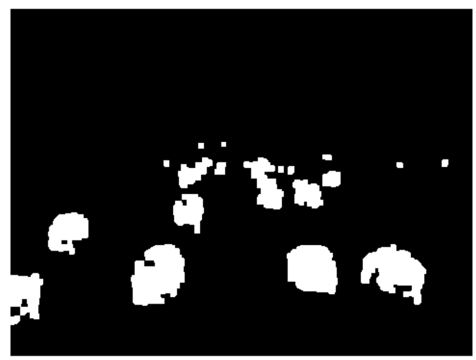

Fig. 5: Resulted Frame The Morphological Operation of Closing

Next, we use the morphological operation of erosion using 6×6 square structural element, so that we can separate the vehicles which their edges are mixed together.
The erosion of A by B is given by the Eq. (7).

$$E(A,B) = A \ominus B = \bigcap_{b\in B} A_{-b} \qquad (7)$$

The resulted image is shown in Fig. (6).

Fig. 6: Resulted Frame After The Morphological Operation of Erosion

Next, we remove the small areas of irrelevant objects around the area of vehicles using 7×7 square structural element of morphological opening operation on the image. Morphological opening is defined according to Eq. (8).

$$A \circ B = (A \ominus B) \oplus B \quad (8)$$

In Eq. (8), $\ominus$ and $\oplus$ denote erosion and dilation, respectively. The resulted image is according to Fig. 7.

Fig. 7: Resulted Frame After Object Detection

2) Finding the Centroids

The Centroid can be said as the center of mass of the object (a geometric figure) of uniform density. It is also known as geometric center and barycenter [11]. The result of the operation of finding the centroid of the vehicles is shown in Fig. 8.

Fig. 8: The Centroid Of the Location of Vehicles

IV. EXPERIMENTAL RESULTS

For testing the proposed method, we used one video traffic surveillance, which this traffic surveillance video is available on the YouTube. Fig. 1 shows an example image used for testing. In test we consider the correct detection of vehicle counting in the total of ten continuous frames. Also we did not consider the far away cars in counting, since that when they get close enough to the camera they will be detected anyway.

Table 1 shows the result of eight tests on the mentioned video traffic surveillance. In Table 1, T denotes the percentage of detected vehicles, and F denotes the number of misdetection of objects in the video as the vehicles.

Table 1: Testing the Proposed Method

Test ID	Number of Vehicles	Number of detected vehicles	T (%)	F (Number)
1	11	10	90.90	0
2	14	11	84.61	1
3	12	9	75	0
4	11	11	100	1
5	11	10	90.90	0
6	11	9	81.81	0
7	14	12	85.71	2
8	10	10	100	1

Average test results shows that the accuracy of our proposed system is approximately 88 percent. It is noteworthy that our system with its high accuracy, is computationally highly efficient and cost effective.

V. CONCLUSIONS

In this paper, we proposed a machine vision system which uses traffic videos to detect and count the vehicles with the aim to better manage their traffic. Our proposed method is superior to other systems since it can be used without the need of any special hardware other than the camera. This allows the system to be implemented cheaply.

The detection accuracy of several frames of our traffic surveillance video, shows the approximate accuracy of 88 percent using our proposed method. Experimental results show the effectiveness of the proposed method to detect the movement of vehicles. However, it should be noted that in any case, all vehicles will be identified in different continues frames.

To improve the proposed method with maintaining its low computational complexity, we can use different edge detection methods or different segmentation methods. Another suggestion to improve the proposed method is to identify the rows of pixels with greater numbers of edges than the other areas of the image. Although the accuracy of the system may increase, the complexity of the system may increase as well.

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