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Background Subtraction Using Coplanar Filter and Quadtree Decomposition for Objects Counting

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Abstract— Generally, background subtraction algorithms are mainly used to find objects in images depending on subtracting these images from known background ones. However, these traditional algorithms cannot detect all edge pixels, where this affects on the accuracy of results. Thus, this paper enhances the traditional background subtraction algorithms based on using two techniques; coplanar filter and Quadtree decomposition. The coplanar filter is used to improve the detection of all edge pixels, while the Quadtree decomposition is used to divide images into homogenous blocks. A car tracking system is then implemented using the MATLAB based on applying both the traditional and enhanced algorithms to detect and count the number of cars in a specific street. A comparison is performed among the detected number of cars by each algorithm and the actual number of cars in that street. The implemented system includes two stages; online and offline. In the online stage, the number of cars in video frames is detected and counted, while in the offline stage, the number of cars in uploaded images from a dataset is detected and counted. Results illustrate this system achieved 47.01% average accuracy rate for the traditional background subtraction algorithm and 81.19% average accuracy rate for the enhanced one, where this proves the efficiency of the presented algorithm.

***Keywords**— Background subtraction; coplanar filter; Quadtree Decomposition; car tracking system; video frames*

I. INTRODUCTION

Recently, various efforts have been performed in the field of computer information systems, where it was proved that the processing of images with the use of computers provides greater flexibility for image processing applications than using electrical resources due to the ability of changing any computer programming in a simple way, where this permits the modification of operations more quickly. [1, 2]

The actual division and tracking of moving objects in video frames is a critical stage in several vision systems, such as human machine interfaces and visual surveillance. The background subtraction algorithm is the mostly used technique to recognize and detect moving objects, where it is based on comparing the pixels of the current frame with those of a background one. Those pixels are then processed to track and localize objects. [1, 2]

Generally, background subtraction algorithms include four stages; preprocessing, modeling of background, detection of the foreground and validation of data. In the preprocessing stage, various image-processing tasks are conducted to convert the input video into a certain format. In the second stage, the preprocessed video frames are used to compute and revise a certain background, module, which offers a numerical explanation of the whole background frame. In the third stage, the video frame pixels that cannot be sufficiently expressed using the background model are determined, where these pixels result as a binary applicant foreground mask. In the last stage, the resulting mask, remove pixels, which are not related to any real moving object, are evaluated, where the final required foreground mask is offered. [2]

Several filters and models have been proposed and used to enhance and ensure the detection of all foreground pixels, such as Weiner filter, median filter, Kalman filter, histograms and Gaussian mixture [3]. However, those filters and models have fixed implementation parameters where this is not adequate for scenes, as traffic intersections that include moving objects at various speeds.

Due to the importance of background subtraction algorithm in tracking moving objects, it must be ensured that all pixels related to the moving objects are correctly and precisely detected and extracted with no missing of any pixel. This is considered as a challenge in the traditional background subtraction algorithms, where the majority of edge pixels cannot be detected. This in turn effects on the accuracy of results and effectiveness of those algorithms. Therefore, this paper presents an enhanced coplanar filter and Quadtree decomposition based background subtraction algorithm to ensure detecting all pixels.

II. RELATED WORKS

In recent years, various background subtraction algorithms have been developed and introduced to detect and counts objects in various scenes. In [1], authors presented a background registration technique to detect moving objects. The number of dynamic objects was detected based on combining simple domain knowledge about object classes with time domain statistical measures to identify target objects in the presence of partial occlusions and ambiguous poses, and the background clutter is effectively rejected.

In [4], authors developed a background subtraction algorithm to count the number of cars on a street. This process offers a binary and a clearer image of foreground objects. Images were preprocessed to reduce noise and shadows and then a morphological gradient operation that uses median filter was used without disturbing the object shape. The implementation was performed using the MATLAB.

In [5], authors presented methods to use the background model in various situations. The presented system can detect the moving and stopped objects. The most used method is the Mixture of Gaussian, which detects the moving object using background subtraction algorithm to let the system detect the moving objects. Authors trained the model and got the adaptive parameter using the time gap between moving and stopped objects.

In [6], authors developed a fuzzy approach for background modeling and background subtraction. A comparison was then conducted between a traditional background subtraction and the developed fuzzy one based on using then in a vehicle detection application. Experimental results demonstrated that fuzzy approach is 6% more accurate than classic approach. However, fuzzy vehicle detection is 12% slower than classic vehicle detection.

In [7], authors developed a system for detecting, and tracking pedestrian and vehicles in traffic intersection using a background subtraction method to be updated and used in real time situation. A blob analysis technique was used to extract binary image facilitates and to detect pedestrians and cars. Based on processing blob's information of relative size and location, pedestrians were distinguished from cars. Applying temporal analysis techniques and moving object detection methods enhanced the system versatility to detect and recognize waiting and moving pedestrians and cars.

In [8], authors presented a method for tracking moving objects in a captured video that taken via locomotive camera in complex views. The sequence of the video may include highly dynamic illumination modification and backgrounds. The developed method composed of four steps. The first step represents stabilizing the video by affine transformation, the second step represents selecting frames in an intelligent way to extract just those frames, which have a large change in the frame' content. Through this step the computational and complexity time reduced.

The third step represents tracking the moving object via "Gaussian mixture" model and "Kalman filter". The fourth step represents recognizing the moving objects via performing Bag of features.

In [9], authors conducted an automatic recognition of objects with using a neural network in the process of recognizing the extracted object and an image processing in the process of detecting and extracting the moving object among a limited area. The implementation consists of three phases; detection of moving objects, extracting detected objects via a group of peremptory rules to find the pixel differences among the detected object(s) image(s) and removing phantom objects, which probably have been gained in the first stage and recognizing the extracted object via a "supervised neural network" depending on a simple algorithm. The algorithm gives solutions for the monitoring secured regions problem.

In [10], authors suggested a general aim method, which includes statistical assumptions besides the knowledge level of animated objects. In the processing stage for the former frames, the shadows and the visible objects (ghosts) were obtained. The moving objects' pixels, shadows and ghosts were processed in a different way in order to provide a selective update based on objects. The suggested approach found the advantage of information of gray color for "both background subtraction" and used it in the process of improving the segmentation of the object. The background subtraction implementation was achieved in two ranges code, which written via Matlab. Then, sets of Simulink blocks have been used.

III. PROPOSED METHOD

This paper introduces the development of an enhanced background subtraction algorithm using both the Coplanar Filter and Quadtree Decomposition. The enhanced algorithm and the traditional one are applied in a designed car tracking system using the MATLAB, which used to detect and count the number of cars in imported videos in the online stage and in uploaded images in the offline stage. A comparison is then performed among the enhanced algorithm and the traditional one based on comparing the number of counted cars in each frame by each algorithm with the actual number of cars in that frame. The main stages of the developed system are demonstrated below:

3.1 Offline stage

In the offline evaluation, images from a defined database are imported to the implemented car tracking system to be evaluated. Both images are then converted into grayscale images. The background subtraction algorithm is then applied, where the difference among both images is computed. This results then in a black (background) and white (foreground) image. The white images are then represented in the original image, where the number of objects (cares) is then detected.

3.2 Online Stage

3.2.1 Importing and Segmentation

In this stage, a video recorded for the traffic in a specific street is imported to the system. This video is then segmented into 500 frames (images). The Fig 1 shows some of these frames.

Figure 1 frames examples

3.2.2 Preprocessing of Frames

After segmenting the input video into frames, each frame is then preprocessed based on resizing it into 650X400 pixels. Then, it is filtered to remove noises based on applying a morphological filter.

3.2.3 Application of Traditional and Enhanced Background Subtraction Algorithm

Both the traditional (blob analysis) and enhanced (Coplanar & Quadtree Decomposition) background subtraction algorithm are applied on the imported video to compare among them.

For the traditional background subtraction algorithm, each one of the processed frames is compared with an image for that traffic without cars based on comparing each pixel in the processed frame with its corresponding pixel in the street image without cars. When the difference among pixels is larger than a certain threshold, the pixel in the processed frame is considered as a foreground one and then it is represented in white in the output image. Else, the pixel is considered as a background one and then it is represented in black in the output image. At the end of this process, a black and white image is obtained, where the white objects represent the cars in that traffic, while the black ones stand for the background. After that, the number of white objects in the final image is counted.

For the enhanced background subtraction algorithm, the coplanar and Quadtree decomposition is initially applied on each frame with the median filter to decrease the salt and pepper noise. After that, noises are removed using the coplanar filter. The square image is then segmented into our square blocks with the same size, where each block is then tested to decide if it meets specific homogeneity criterion or not. When the block meets that criterion, it is not segmented again. Else, it is sub-segmented into other four blocks, where the test is then applied on each block and so on. This procedure is repeated till each one of the blocks meet the specified criterion. After completing the iteration process, the number of in each frame cars is counted based on finding the number of elements in the traced region boundaries in that frame.

IV. RESULTS

The following subsections illustrate the obtained results of both stages; online and offline.

4.1 Results of Offline stage

Initially, a background image and a test one are imported to the system as the ones shown int Fig 2.

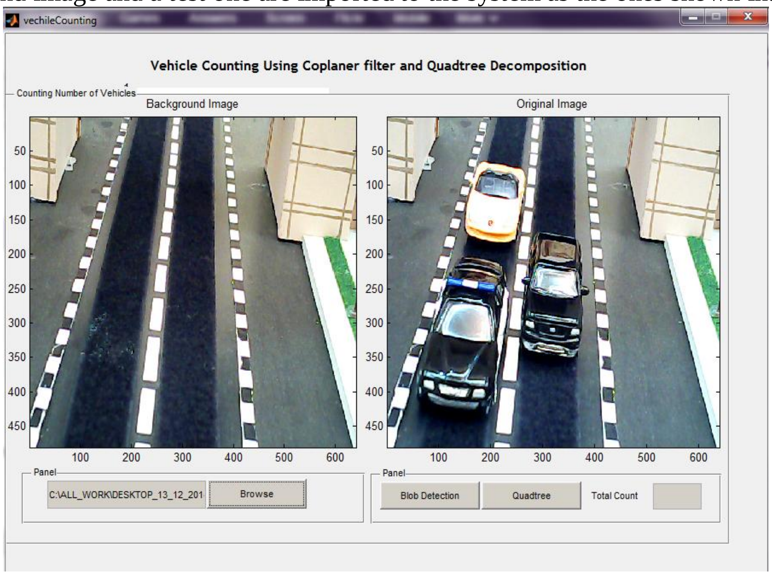


Fig 2 Background and test images

Both images are then converted into grayscale images as shown Fig 3.

Fig 3 Grayscale background image

The resultant grayscale test image and the result of applying the Quadtree decomposition to detect cars are shown below. As shown the number of cars is 3 and the results of Quadtree decomposition gives output 3 also.

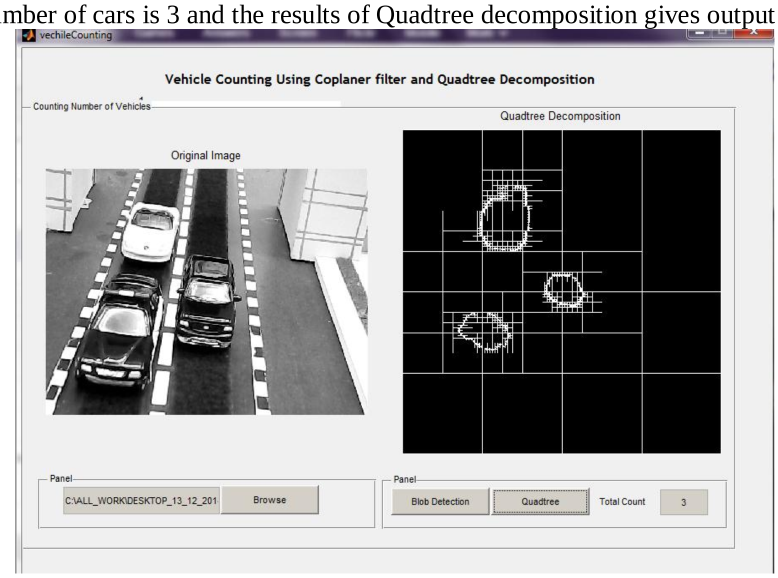


Fig. 4 grayscale test image and the result of applying the Quadtree decomposition

After that, the difference among both images is computed, where the resultant black and white image is illustrated in the Fig. 5. The Fig. 5 also shows the representation of the detected foreground objects (cars) on the original test image. As shown below, the counted number of cars is 4, while the actual number of cars is 3

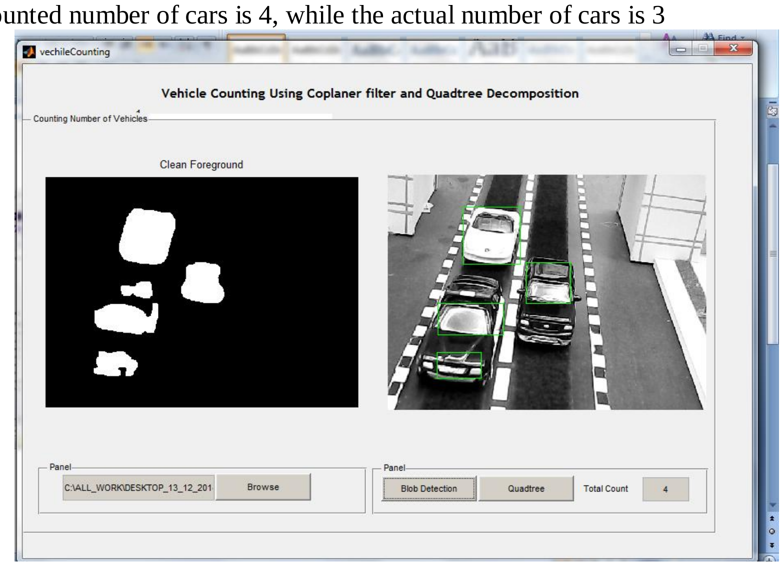


Fig. 5 Black and white output image

4.2 Results of Online stage

In this stage, a recorded video is imported to the implemented system in both cases; traditional and enhanced background subtraction algorithm. The video is segmented into frames where each frame is then compared with a defined background image in both cases. The system in both cases counts the number of cars in the street.

A comparison among both algorithms based on the number of cars in frames is demonstrated below.

- **Detection of one car**

As shown in the table 1, the traditional algorithm fails in detecting one car, while the enhanced algorithm detects the car in both sides and provides 100% detection accuracy.

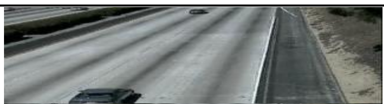
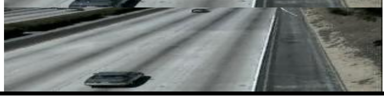
Table 1 Results of detecting one car

Frame	No. of counted cars by the traditional algorithm	No. of counted cars by the enhanced algorithm	Real no. of cars	Accuracy of the traditional algorithm	Accuracy of the enhanced algorithm
	0	1	1	0%	100%
	0	1	1	0%	100%

- **Detection of two cars**

As shown in the table 2, the traditional algorithm average accuracy in detecting two cars is 25% , while the enhanced one detects the car in both sides offers 75% detection accuracy.

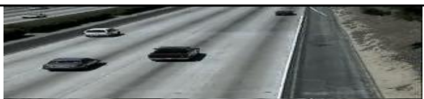
Table 2 Results of detecting two cars

Frame	No. of counted cars by the traditional algorithm	No. of counted cars by the enhanced algorithm	Real no. of cars	Accuracy of the traditional algorithm	Accuracy of the enhanced algorithm
	1	2	2	50%	100%
	1	2	2	50%	100%

- **Detection of five cars**

As shown in the table 3, the traditional algorithm average accuracy in detecting five cars is 55% , while the enhanced one detects the car in both sides offers 95% detection accuracy.

Table 3 Results of detecting five cars

Frame	No. of counted cars by the traditional algorithm	No. of counted cars by the enhanced algorithm	Real no. of cars	Accuracy of the tradition al algorith m	Accuracy of the enhanced algorithm
	3	5	5	60%	100%
	4	5	5	80%	100%

- **Detection of seven cars**

As shown in the table 4, the traditional algorithm average accuracy in detecting seven cars is 53.56% , while the enhanced one detects the car in both sides offers 82.13% detection accuracy.

Table 4 Results of detecting seven cars

Frame	No. of counted cars by the traditional algorithm	No. of counted cars by the enhanced algorithm	Real no. of cars	Accuracy of the traditional algorithm	Accuracy of the enhanced algorithm
	4	6	7	57.14%	85.71%
	3	5	7	42.85%	71.42%

- **Detection of nine cars**

As shown in the table 5, the traditional algorithm average accuracy in detecting nine cars is 69.43% , while the enhanced one detects the car in both sides offers 83.32% detection accuracy.

Table 5 Results of detecting none cars

Frame	No. of counted cars by the traditional algorithm	No. of counted cars by the enhanced algorithm	Real no. of cars	Accuracy of the traditional algorithm	Accuracy of the enhanced algorithm
	6	9	9	66.66%	100%
	6	7	9	66.66%	77.77%

It can be noted from the tables above that the enhanced background subtraction algorithm outperforms the traditional one in the accuracy of counting the number of cars in the frames. The average accuracy of the traditional algorithm for all frames is 47.01%, while it is 81.19% for the enhanced algorithm.

V. CONCLUSION

This paper introduces the development of an enhanced background subtraction algorithm based on using both the Coplanar Filter and Quadtree Decomposition. This algorithm and a traditional one are applied to implement a car tracking system using the MATLAB program to count the number of cars in a specific street. Two evaluation stages; offline and online stages are applied to assess the performance of the implemented system. The frames of the imported video include several numbers of cars. These counted numbers by each algorithm are then compared with the actual number of cars for each frame to determine the optimal background subtraction algorithm. Results show that the enhanced background subtraction algorithm outperforms the traditional one in the accuracy of counting the number of cars in all frames. The resultant average accuracy of the traditional background subtraction algorithm is 47.01%, while it is 81.19% for the enhanced one.

VI. FUTURE WORKS

This work can be enhanced in the future based on performing the following:

- Applying the implemented system on videos recorded for cars in two-side streets.
- Importing videos for cars with various sizes.
- Enhancing the system to detect and count cars and other objects in the same time.
- Applying other preprocessing stages for more enhancement of images.
- Enhancing the system to detect and track the motions of objects in video.

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