Vehicle Counting Method Based on Digital Image Processing Algorithms

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***Abstract*- Vehicle counting process provides appropriate information about traffic flow, vehicle crash occurrences and traffic peak times in roadways. An acceptable technique to achieve these goals is using digital image processing methods on roadway camera video outputs. This paper presents a vehicle counter-classifier based on a combination of different video-image processing methods including object detection, edge detection, frame differentiation and the Kalman filter. An implementation of proposed technique has been performed using C++ programming language. The method performance for accuracy in vehicle counts and classify was evaluated, which resulted in about 95 percent accuracy for classification and about 4 percent error in vehicle detection targets.**

Keywords*- *Vehicle Counting, Vehicle Detection, Traffic Analysis, Object Detection, Video-Image Processing.

I. INTRODUCTION

Nowadays traffic problems are increasing due to the fast growing number of vehicles. Traffic flow analysis can play a fundamental role in gathering essential information about roads and passing vehicles. These data can be useful for identifying critical flow time periods or determining the influence of large vehicles or pedestrians on vehicular traffic flow, and even documenting the traffic volume trends. This useful information can also be used for better traffic management methods, such as changing the timings of traffic lights based on traffic flow. There are several ways to count the number of vehicles passed in a period of time, and therefor estimate the traffic flow, such as using manual counters, portable counters and observers. But nowadays it is demonstrated that using camera-based systems are better choices for traffic flow estimation purposes [20].

In the past decade, image processing and machine vision algorithms have been applied for roads/highway traffic analysis as an alternative method which neither placement of a sensor object in the roadway, nor direct camera control by human is needed [1]. In these software-based vehicle detectors, the output of video cameras installed alongside roadways are processed [32]. Tracking moving vehicles in the roadway videos prepare an acceptable description of traffic flow and absence or presence of vehicles in the video sequence. In fact, vehicle tracking is the process of finding the location of a vehicle in each frame of the video sequence.

This article focuses on a software-based novel technique for vehicle detection in roadways and classification of passed vehicles in different specified types. This method detects vehicles in the input video stream, assigns an exclusive identifier for each of them, classifies each vehicle on its distinctive vehicle-type group and finally counts them all. The developed method was implemented in a software platform which resulted in less error percentage and better accuracy. In addition, the method was evaluated and the performance analyzed using a real condition roadway video feed.

This paper is organized as follows. Section II, gives a suitable background on essential definitions and techniques associated with proposed work. Section III discusses related works which has been performed and their methodologies. And finally section IV and V present proposed method and two different experiments, respectively.

II. BACKGROUND INFORMARION

A. Video Processing

Video processing is a subcategory of Digital Signal Processing techniques where the input and output signals are video streams. In computers, one of the best ways to reach video analysis goals is using image processing methods in each video frame. In this case, motions are simply realized by comparing sequential frames [7]. Video processing includes pre-filters, which can cause contrast changes and noise elimination along with video frames pixel size conversions [6]. Highlighting particular areas of videos, deleting unsuitable lighting effects, eliminating camera motions and removing edge-artifacts are performable using video processing methods [29].

B. RGB to Grayscale Conversion

In video analysis, converting RGB color image to grayscale mode is done by image processing methods. The main goal of this conversion is that processing the grayscale images can provide more acceptable results in comparison to the original RGB images [11]. In video processing techniques the sequence of captured video frames should be transformed from RGB color mode to a 0 to 255 gray level. When converting an RGB image to a grayscale mode, the RGB values for each pixel should be taken, and a single value reflecting the brightness percentage of that pixel should be prepared as an output [2].

C. Power-law Transformation

Enhancing an image provides better contrast and a more detailed image as compare to a non-enhanced one. There are several image enhancement techniques such as power-law transformation, linear method and Logarithmic method. Image enhancement can be done through one of these grayscale transformations. Among them, power-law

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transformation method is an appropriate technique which has the basic form below:

$$V = A\, v^{\gamma} \qquad (1)$$

Where V and v are output and input gray levels, γ is Gamma value and A is a positive constants (in the common case of A=1). Consequently, choosing the proper value of γ can play an important role in image enhancement process and preparing suitable details identifiable in image.

D. Sobel Edge Detection

Object detection can be performed using image matching functions and edge detection. Edges are points in digital images at which image brightness or gray levels changes suddenly in amount [33]. The main task of edge detection is locating all pixels of the image that correspond to the edges of the objects seen in the image.

Among different edge detection methodologies, Sobel algorithm is a simple and powerful edge detection method. To recognize edge pixels in this technique, suppose that the pixel I (i, j) has been surrounded by 8 neighbors, P_1 to P_8, as shown in Table 1 [9]:

TABLE1 AN EDGE PIXEL AND ITS 8 NEIGHBORS

P_1	P_2	P_3
P_4	I (i,j)	P_5
P_6	P_7	P_8

Now I (i, j) is an edge pixel if:

$$I_{(i,j)} = (u^2 + v^2)^{1/2} \qquad (2)$$

Where

$$u = (P_6+2P_7+P_8) - (P_1+2P_2+P_3) \qquad (3)$$

And

$$v = (P_3+2P_5+P_8) - (P_1+2P_4+P_6) \qquad (4)$$

This process changes the location of the 3x3 matrix with the current pixel as the window center. After that, a threshold is used to recognize the pixel placed on an edge. In this case, the magnitude response claims an edge point only if the Sobel magnitude remains above the threshold [12].

E. The Kalman Filter

Images typically have a lot of speckles caused by noise which should be removed by the means of filtration. The Kalman filter is a powerful and useful tool to estimate a special process using some kind of feedback information [14]. The Kalman filter is used to provide an improved estimate based on a series of noisy estimates.

This filter specifies that the fundamental process must be modeled by a linear dynamical structure:

$$x_k = F_{k-1}x_{k-1} + w_{k-1} \qquad (6)$$

$$y_k = H_k x_k + v_k \qquad (7)$$

Where x_k and y_k are the state and measurement vectors, w_k and v_k are the process and measurement noise, F_k and H_k are the transition and measurement values and k is desired time step [28]. The Kalman filter also specifies that the measurements and the error terms express a Gaussian distribution, which means in vehicle detection each vehicle can only be tracked by one Kalman filter [22], [31]. Therefore the number of Kalman filters applied to each video frame depends on the number of detected vehicles.

III. PREVIOUS WORKS

Using image/video processing and object detection methods for vehicle detection and traffic flow estimation purposes has attracted a huge attention for several years [5]. Vehicle detection/tracking processes have been performed using one of these methodologies [8]:

- Matching
- Threshold and segmentation
- Point detection
- Edge detection
- Frame differentiation
- Optical flow methods

It can be said that one of the most important researches in object detection fields, which has resulted in the auto-scope video detection systems is introduced in [15]. In some works such as [21], forward and backward image differencing method used to extract moving vehicles in a roadway view. Some studies like [17] and [4] proved that the use of feature vectors from image region can be extremely efficient for vehicle detections goals. Some others represented the accurate vehicle dimension estimation using a set of coordinate mapping functions as it can be seen in [16]. Furthermore, some studies have developed a variety of boosting algorithms for object detection using machine learning methods which can detect and classify moving objects by both type and color such as [18] and [19]. Named approaches have both their advantages and disadvantages.

IV. PROPOSED TECHNIQUE

Different from previous works, the method proposed in this paper uses a combination of both “Frame Differentiation” and “Edge Detection” algorithms to provide better quality and accuracy for vehicle detection. By using the Kalman filter, position of each vehicle will be estimated and tracked correctly. This filter also used to classify detected vehicles in different specified groups and count them separately to provide a useful information for traffic flow analysis. The flowchart of the method is represented in Figure 1.

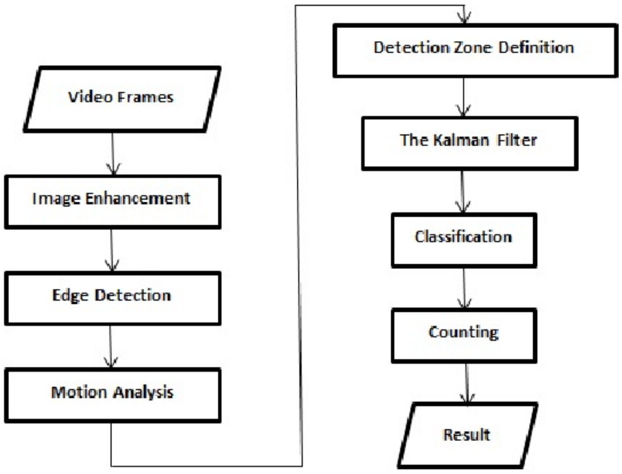

Figure 1. Flowchart of the technique

Based on Figure 1, the technique includes these steps: image enhancement process, edge detection, motion analysis using a combination of different techniques, detection zone definition, the Kalman filter, vehicle type classification and counting. It is necessary to say that some assumptions made in this work:

- No sudden changes of directions are expected
- No car accidents and crashes are expected
- There is both physical and legal limitations for vehicles
- motion scenes are captured with a view from above to the roadway surface

The proposed technique to detect and count vehicles is presented as below:

A. Grayscale Image Generation and Image Enhancement

To get better results, vehicle detection process should be performed in the grayscale image domain. Hence a RGB to grayscale conversion is performed on each video frame. To achieve an appropriate threshold level and make results more suitable than the input image, each frame should be brought in contrast to background. Among several grayscale transformations, power-law method has been used in this work. Experimental results in different situations showed that the best results appear when γ value is set to 1.2 as it can be seen in Figure 2. This figure shows the result of applying different γ values to grayscale converted image, where section *A* is the input RGB color frame and *B*, *C* and *D* are grayscale versions with gamma values *0.2*, *2.2* and *1.2*, respectively.

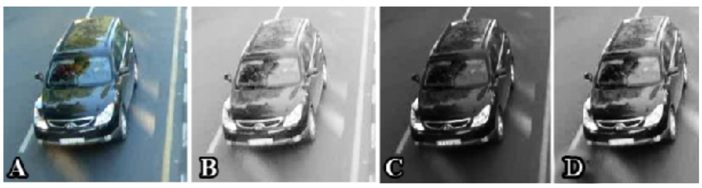

Figure 2. Input RGB video frame (A) and grayscale converted with different γ values (B, C and D)

B. Edge Detection

Each image (video frame) has three significant features to achieve detection goals. These features include: edges, contours and points. Among mentioned features, an appropriate option is to use edge pixels. Processing of image pixels enables us to find edge pixels, which are the main features of passing vehicles in a roadway video frame. One of the most common ways to find the edges of an image is to use Sobel operator which has been used in this work.

The result based on equation (2) is presented in Figure 3. As it can be seen the output result of edge detection process is demonstrated in a binary image (threshold) with the detected edge pixels.

Figure 3. A: Original image B: Edge detection result

The next step is to extract moving edges from sequential video frames and process the resulting edge information to obtain quantitative geometric measurements of passing vehicles.

C. Background Subtraction

Using provided threshold, the static parts of sequential video frames should be cleaned. The main challenge here is that the performance of image analysis algorithms suffers from darkness, glare, long shadows or bad illumination at night, which may cause strong noises [3], [13]. Therefore, the grayscale image might be unspecified in these situations and make the detection task a bit more complex.

Edges essentially separate two various regions which are static region (the roadway) and dynamic region (moving vehicles). The static background is then deleted to locate moving objects in each frame. The result zone leaves only vehicles and some details as moving objects in sequential images which are changing frame to frame.

A combination of forward and backward image differencing method and Sobel edge detector has been used in this work. According to this method, three sequential frames are chosen and the middle one should be compared to its previous and next frames. Consequently, extracted edges of each frame detected by Sobel operator achieved from previous section are used here. Then the differences of frames can be obtained by subtracting each two sequential pair of generated binary images, as in equation 5:

$$\textbf{\textit{BinaryImage}}\ (Sobel\ (F_{n-1}) \cap Sobel\ (F_n)) - \textbf{\textit{BinaryImage}}\ (Sobel\ (F_n) \cap Sobel\ (F_{n+1})) \qquad (5)$$

Where F_{n-1} is previous frame, F_n is current frame and F_{n+1} is the next frame. This process continues to the last three sequential video frames. The output result is demonstrated in Figure 4. In this figure A, B and C represent three sequential frames, where D demonstrates the output background subtraction method. Using this technique moving vehicles are detected in three sequential frames.

Figure 4. Proposed moving vehicle detection technique

D. Detection Zone

As an observation (detection) zone, a region should be defined to display moving vehicle's edges in a bounding box at the time that the vehicle enters it. This zone is in the middle of the screen and covers 1/3 of its height and 3/5 of its width (considering minimum and maximum available size of detectable passing vehicles in pixels). This area which contains the most traffic can embed both small and long vehicles and the main goal of defining it is to avoid perspective challenges and wrong type counts. Based on proposed method in background subtraction level, a vehicle is detected in three sequential frames. When a moving vehicle is detected, a bounding box whelming vehicle borders in binary image is drawn. Figure 5 demonstrates all the details about the detection zone. According to this figure, border No.1 specifies entrance of the detection zone, so the car with label "A" cannot be detected because it hasn't entered into the area. Area No.2 which is colored, can detect any moving vehicles. So the cars with labels "B" and "C" are tracking and detecting in the current frame. Tracking process continues until they leave the zone. Border No.3 is the end of detection zone and ends tracking function of crossing vehicles.

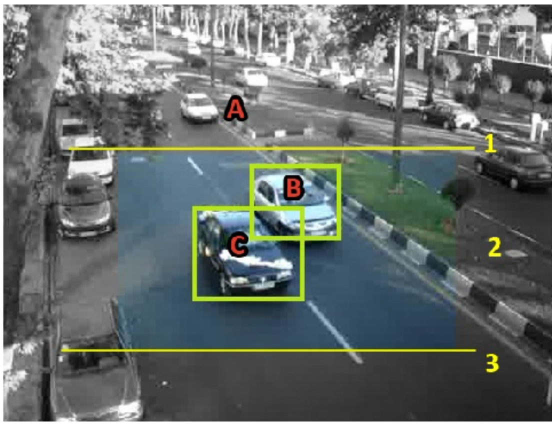

Figure 5. Proposed detection zone

E. The Kalman Filter

The bounding boxes could also be used to count and classify passing vehicles. This can be done by the Kalman filtering technique. In roadway videos, the edge detection function provides an inaccurate position of moving vehicles, but the knowledge of the vehicle's current position needs to be improved. Since perfect measurements cannot be guaranteed due to movement of objects, the measurements should be filtered to produce the best estimation of the accurate track.

The Kalman filter can optimally estimate the current position of each vehicle and also predict the location of vehicles in future video frames by minimizing noise disorders. It is also used to stop tracking of vehicles proceeding in opposite direction in roadway captured video. Although edge detection can find moving objects, the Kalman filter makes an optimal estimate of positions based on a sequence of localization measurement.

The linear Kalman filter is simpler and used in proposed technique. Consider parameter A as area of vehicle's bounding box, which has been detected in frame differentiation phase and p(x, y) is the center point of the vehicle where x and y are its distances from horizontal and vertical edges. Now by integration of proposed parameter in (6) and (7) equations resulted in the following vectors [30]:

$$x_k = [x, y, A, vx, vy, vA]^T \qquad (8)$$

$$y_k = [x, y, A]^T \qquad (9)$$

Where v_A is the rate of changes in vehicle's bounding box, v_x and v_y are the speed of changes in the movement of vehicle's center point. Subsequently using the Kalman filtering technique, the position of each vehicle can be estimated and tracked better. Finally an identifier is allocated to each passing vehicle for counting and classification purposes.

F. Counting and Classification Functions

Vehicle counters are used in computing capacity, establishing structural design criteria and computing expected roadway user revenue [10]. Typically in proposed technique vehicles are classified as four common types:

- Type1: bicycles, motorcycles
- Type2: motorcars
- Type3: pickups, minibuses
- Type4: buses, trucks, trailers

It is necessary to have the width and length of each vehicle's bounding boxes in pixels to diagnose that the passing vehicles belongs to which of the mentioned types. The area of each bounding box shows that which type should be allocated for the vehicle. Each vehicle type can be shown by a special rectangle color. In this work as it is demonstrated in Figure 6, Type 1 has been represented by red, where Type2, Type 3 and Type 4 have been characterized by green, blue and yellow recatngles, respectively.

Figure 6. Vehicle classification colored bounding boxes

In counting step, four isolated counters used for each vehicle type and a total counter is needed to store the sum value of them. All counters should count just the vehicles which are passing in a specific direction. So if a vehicle stops, turns or moves in wrong direction in the detection zone, it should not be counted. In this technique, counting is according to the number of moving vehicles detected in the detection zone and classified in one of mentioned groups.

Figure 7. Counting similar vehicle types

Figure 7 displays some useful information obtained by this vehicle detection technique. Total passed vehicles, which shown in yellow, helps to analyze traffic flow in a period of time. Also by calculating the bounding boxes height and width in pixels, vehicle types have been distinguished and counted by related counters. Some of the interesting aspects of obtaining results, which presented in Figure 7 are that both detected cars are moving in similar directions, both have been placed in detecting zone, while the rear white vehicle has not been counted. Furthermore, in both counted vehicles, edges have covered with green rectangles, which shows that they belong to Type 2 (even the green numbers inside bounding boxes confirm this result).

V. Experimental Results

A real-condition test has been performed for validation and efficiency measurement of the proposed method. An input video with AVI format and 29 frames per second frame rate has been collected. The resolution of the video was 960*540 and it included 124 passing vehicle in about 3:06 minutes. The presented technique has been implemented using C++ programming language and Open-CV version 2.4.8 library. In addition, the real number of passed vehicles in the video which has been calculated manually was 15 of Type-1, 78 of Type-2, 22 of Type-3 and 9 of Type-4.

Experiment process was divided into 2 separate sections: a vehicle count accuracy test (detection test) and a vehicle classification accuracy test. Each experiment resulted in as follows.

1. Detection test

In this test, the accuracy of the technique in counting the number of vehicles has been analysed. The outcome resluts are shown in Table 2.

Table 2 Detection Test Results

Real number of passed vehicles	Counted number of vehicles by the method	Number of errors
124	119	5 (4%)

The detection test results showed that 3 of 5 errors occurred in the conditions that two moving vehicles with similar colors and sizes were moving close to each other. Consequently the technique could not distinguish subjects in such conditions. Such errors can be handled using methods recommended in several manuscripts [23], [24], [25].

Based on test results another important challenge of the technique was to avoid counting nonvehicle moving objects such as people or animals crossing the roadway, which have caused remained 2 errors. To handle this challenge, some basic factors should be considered:

1) Motion Speed: usually in highways drivers are faced with speed limitations like maximum and minimum speed. Hence, if there was not a heavy traffic or car accident, the detected moving object with low speed must be humans or passing animals and should not be counted or classified.

2) Motion Direction: the direction of moving vehicles differs from animals or humans passing across the roadway, which can be a suitable factor to distinguish them from each other.

2. Classification test

The second test has been performed to analyze the accuracy of vehicle classification part. Based on the detection test, 119 vehicles have been counted which is considered in this experiment. Consequently, a confusion-matrix has been provided to summarize the results and visualize the performance of testing the technique, which can be seen in Table 3.

Table 3 Confusion (Matching) Matrix for Performance Visualization

	Bicycles, motorcycles	*Motorcars*	*Pickups, minibuses*	*Buses, trucks, trailers*
Bicycles, motorcycles	*13*	*1*	*0*	*0*
Motorcars	*1*	*71*	*3*	*0*
Pickups, minibuses	*0*	*1*	*18*	*1*
Buses, trucks, trailers	*0*	*0*	*1*	*8*

Hence the accuracy of the method can be obtained by Table 3:

$$\text{Accuracy} = \frac{13+71+18+8}{14+75+20+9} = \frac{113}{119} = 0.949$$

Which results in about 5 percent of classification error. Misdiagnosis results can be eliminated using these solutions:

- Choosing an appropriate detection zone which can embed even long vehicles like trailers and buses
- Using pattern recognition methods to teach the technique all different vehicle types by their structural shapes [26], [27]

- Using a combination of vehicle shape and occupy pixels
- Defining isolated detection areas for each roadway vehicle lines

Although the proposed technique faced with some challenges, the errors are partly appropriate and do not affect the traffic flow intensity. That is because just an estimation magnitude of traffic flow is needed for control and analysis goals.

VI. CONCLUSIONS

In this paper a vehicle counting technique based on image processing algorithms has been presented. This method led to reduce the costs –because of being a software based solution- besides having the quality and accuracy. Also it was able to classify passing vehicles in roadways using a combination of image processing methods and the Kalman filter algorithm. Experimental results indicated that presented method worked effectively. The classification test error was about 5 percent and detection test error was about 4 percent made it suitable for vehicle detection and traffic flow analysis purposes.

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