A Simple Method for Calculating Vehicle Density in Traffic Images

[1]Tahere. Royani, [2]Javad. Haddadnia, [3]MohammadReza.pooshideh
[1,2,3]Electrical Engineering faculty, Tarbiat Moallem University of Sabzevar, Iran
E-mail: Haddania@sttu.ac.ir; tahere.royani@gmail.com; M.poshideh@gmail.com

Abstract: *Calculating of vehicles density in traffic images is a challenging research topic as it has to directly deal with hostile but realistic conditions on the road, such as uncontrolled illuminations, cast shadows, and visual occlusion. Yet, the outcome of being able to accurately count and resolve vehicles under such conditions has tremendous benefit to traffic surveillance. Accurate vehicle count enables the extraction of important traffic information such as congestion level and lane occupancy. There are different methods for vehicles counting from traffic images that emphasize on the accuracy, but most of them suffer from long time process and computational complexity, so they can't be used in real-time condition. This paper proposed a novel simple method for traffic density calculation in multiple vehicle occlusions based on counting object pixels and assigning a distance index to each region of image that concentrates on time and computational complexity and has tolerable accuracy in traffic density calculation. Suppose that the occluded vehicles are segmented from the road background by previously proposed vehicle segmentation method. The proposed method has been tested on real-world monocular traffic images with multiple vehicle occlusions. The experimental results show that the proposed method can provide real-time and useful information for traffic surveillance.*

Keywords: vehicle density, computational complexity, traffic surveillance.

1. Introduction

Intelligent Transportation System (ITS) has become an active research area where artificial intelligence techniques are extensively applied to enhance safety and effectiveness on the road. An intelligent traffic control system involves the collection of data describing the characteristics of vehicles and their movement through road networks. Vehicle counts, vehicle speed, vehicle path, flow rates, vehicle density, vehicle length, weight, class (car, van, bus) and vehicle identity via the number plate are all examples of useful data. Such data may be used for law enforcement, automatic tolls, congestion and incident detection and increasing road capacity via automatic routing and variable speed limits. There are different methods for data collection that are normally based on inductive loop detector, infrared detector, radar detector or video-based solution. In recent years, the traffic surveillance systems have become a worldwide hot topic because it can provide meaningful and useful information such as over-speed and violation in traffic. Video-based systems offer many advantages compare to other techniques, such as more traffic information obtained, easily installed, scalable with progress in image processing techniques, etc. Furthermore each of these systems can service one lane only. In contrast, video systems can be mounted at a side view position and a single sensor is able to monitor several lanes simultaneously [1]-[5]. The main disadvantages of video based systems are the huge digital processing power needed to extract the essential information from the video image data [6]. However, video-based solutions for outdoor environments are easily influenced by falling weather, variant illumination, moving shadows and small motion changes caused by wind or other factors. Of all the problems that are associated with outdoor tracking, visual occlusion presents the biggest obstacle especially in vehicle count and vehicle density calculation. Yet, the outcome of being able to accurately count and resolve vehicles under such conditions has tremendous benefit to traffic surveillance [7]. A partial solution may be obtained by setting the camera's optical axis perpendicular to the road plane; this configuration severely reduces the range and amount of visual information available, as compared with a perspective camera configuration [8]. An alternative solution is to use more than one camera (i.e., stereo vision) [9] or use non-visual sensors such as inductive loops or laser sensors in addition to the visual sensors to aid the vision system [10], [11].

There are different algorithms that can be broadly classified as follows: model-based, region-based, active contour-based, feature-based, and probabilistic based. [7]. Such as the proposed method in [7], can accurately count the number of vehicles that involved in occlusion, but didn't concentrate on the time and computational complexities, unfortunately suffered from this problem and can't be used in real-time applications. The purpose of this paper is to propose a new method for calculating the vehicle density (not vehicle counting) in heavy traffic condition that emphasizes on the time and computational complexity and its accuracy is almost good.

The rest of this paper is organized as follows: a brief vehicle segmentation and image binarization in Section II, The proposed method is detailed in Section III, the result and discussions are presented in Section IV, and conclusion can be found in Section V.

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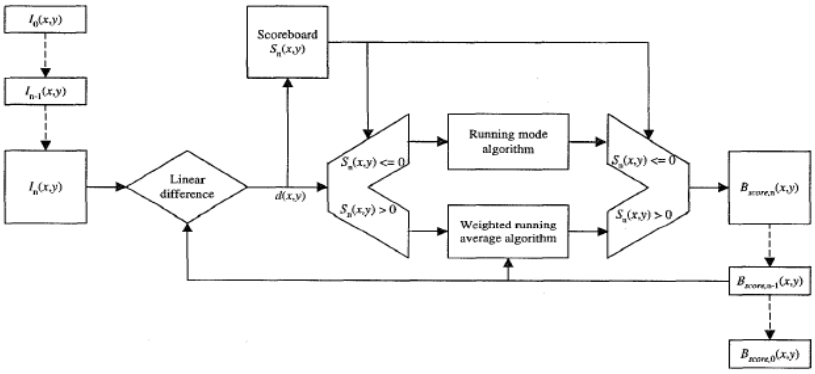

Fig. 1: Block diagram of Scoreboard algorithm.

2. Vehicle segmentation and image binarization

2.1. Background Estimation

Successful video-based systems for urban traffic monitoring must be adaptive to different conditions; they should include algorithms for detection of moving vehicles and short-term stood-still vehicles (especially important in urban environments). Therefore, foreground/background discrimination and mechanisms for providing relative robustness against progressive or sudden illumination changes (auto iris mechanism may have a significant effect in the latter) should be also considered [12]. There are different methods for adaptive background estimation such as average method [13], using kalman filter in background estimation [14], and so on.

In this paper the "scoreboard algorithm" from [15] is employed for this purpose, as it is fast and accurate for estimating the stationary background.

2.2. Scoreboard Algorithm

The algorithm employs the running mode and running average algorithms, which are two commonly used algorithms, as the estimation core. A scoreboard is used to keep the pixel variations in the image sequence and is used to select between the running mode and the running average algorithm in each estimation step. Algorithms based on the running mode are reputed to be quite accurate but their computing speed is so slow that none of them are considered for real-time applications. On the other hand, running average algorithms are inherently fast but their estimation accuracy is poor, so the proposed background estimation algorithm has excellent performance in terms of estimation accuracy and speed [15].

Fig.1 depicts the block diagram of the scoreboard algorithm. Fig. 2(a) shows traffic frames, background estimation [Fig. 2(b)] estimates the background from the images.

2.3. Vehicle Segmentation and binarization

In the next step, after background subtraction vehicle segmentation segments the vehicle from the background. Fig.3 (b) shows the result of segmentation of a traffic image [Fig. 3(a)]. By use of a good threshold that usually obtains from experimental result (about 25), the new segmented image has been changed to binary. By use of an average filter, noise of image has been deleted. After that, the extra region of binary image has been deleted. Fig. 4 shows the results of these processes.

Fig.2. a) Traffic frames, b) estimated background

Fig.3. a) A traffic image, b) Vehicle segmentation

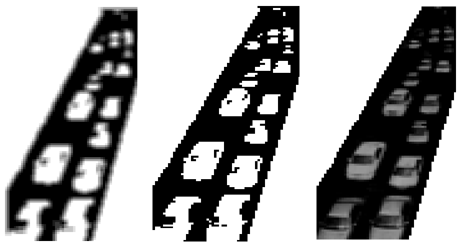

Fig.4. From right: extra region deletion, binarization, noise elimination

3. Proposed method

3.1. Camera Model and Assumptions

In traffic surveillance system, we assume that, the position of camera is fixed .The pinhole camera model is assumed for our algorithm. This model allows for more simplistic calculation of camera properties such as angle of view. We are also assuming a perfect lens model to simplify the calculation related to the digital image produced by the camera.

3.2 Adaptive Vehicle Size Fitting

For a fixed camera configuration, in imaging geometries where the road is along the z-axis of the camera, vehicles further away from the camera are expected to be smaller in size (Fig. 5). The adaptation of the vehicle size depends on the relative position of the camera with respect to the road [16].

Our method of distance calculation relies on the notion that if the distance of an object from the lens, R is changed by ΔR in one direction (R' = R +ΔR, where R' is the new distance of the object), then the size of the image, h_I, is also changed by a function of ($h_I' = h_I + f(\Delta R)$, where h_I' is the new size of the image) (Fig.6). Equation (1) shows that the image size is determined by the focal length f of the lens and the distance of the lens from the object R.

$$h_I = h_O \times \frac{f}{R-f}, R > f \tag{1}$$

If we increase the distance of the object from lens by ΔR, then the size of the image becomes:

$$h_I' = h_O \times \frac{f}{R+\Delta R-f}, R > f \tag{2}$$

$$\frac{h_O}{h_I'} = \frac{R-f}{f} + \frac{\Delta R}{f}, R > f \tag{3}$$

We suppose, at the point of initializing, R=2f, then h_I=h_o and the size of the image becomes:

$$\frac{h_O}{h_I'} = 1 + \frac{\Delta R}{f}, R > 2f \rightarrow h_I' = h_O \frac{f}{1+\Delta R} \text{ or} \tag{4}$$

$$h_I' = h_I \frac{f}{1+\Delta R}, R > 2f$$

Also, we know if we increase the size of the object by δ and keep the object at the same distance from the lens, then the size of the image becomes:

$$h_I' = h_I + \delta \times \frac{f}{R-f}, R > f \tag{5}$$

When we keep the object at the same distance, $\frac{f}{R-f}$ is a constant and therefore the change in size of an object will cause a linear change in the size of the image. Therefore, the conversion from actual distance in meter or feet to pixel difference is governed by a linear relationship (Fig.7) [17].

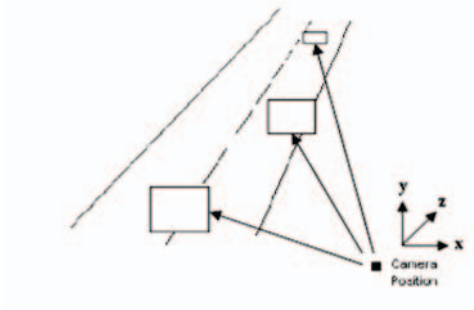

Fig.5. Adaptation of vehicle sizes for a fixed camera set-up

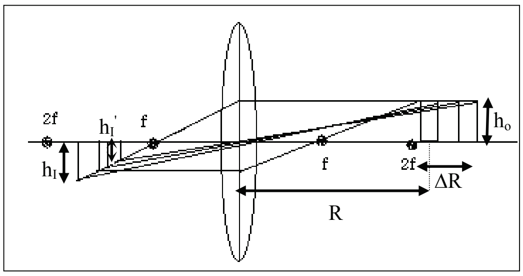

Fig.6. image size changing with change of object distance from lens

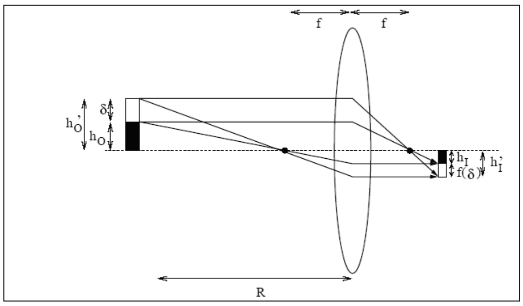

Fig.7. image size changing with changing an object size

3.2. Vehicle density calculation

According to the last paragraph by use of “Equation (4) ”, and “Equation (5) ”, we can calculate real size of vehicles in an image in pixel, and with counting the number of white pixels with purposing their shrinking rate and divided to number of one vehicle pixels, the vehicle density in a scene will be calculated. For this we divide the area to proportionate regions "about length of a sedan", thus vehicle density is calculated by using “Equation (6)”.

$$V = \left(\sum_{i=1}^{n} p_i \left(\frac{1+\Delta R_i}{f}\right)\right) \Big/ p \tag{6}$$

Refer to “Equation (6)”, n is the number of regions in scene, p_i is the number of white pixels in related region i, and p is size of vehicle image in reference point (R=2f) or size of vehicle in pixel. By summation all white pixels with purposing their shrink rate, the vehicle density with a good accuracy is estimated.

4. Result and discussion

For testing this method we must know the focal length of our camera and changing rate of image from meter to pixel. This method has been tested on the existent database and results show that, the proposed system can provide real-time and useful information with good accuracy and short processed time. Fig. 8 shows the subdivision of an image. Table 1 gives the comparison of results estimated for different video sequences.

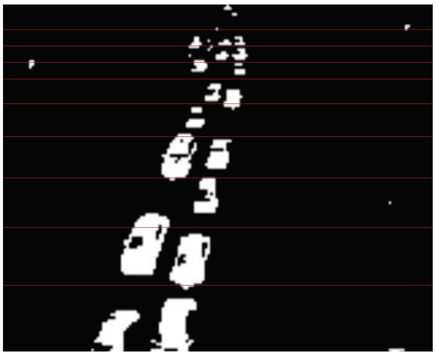

Fig.8. Result of divided image

TABLE I: Result for different video sequences

image	vehicle	count	Error positive	Error negative	Accuracy (%)
Case 1	15	14	1	0	93.4%
Case 2	20	22	0	2	90%
Case 3	25	23	2	0	92%
Case 4	12	12	0	0	100%
Average					93.85%

Computational time of proposed method is depicted in Table 2, it compared with the method was proposed in [7]. Both methods were implemented in MATLAB. It is noticeable that computational time of proposed method is very short and as such, the proposed method is computationally feasible.

TABLE II: computational time for different method

method	Computational time
Method in[7]	2.5s
Proposed method	300ms

5. Conclusion

In the present work, a new method for vehicle density calculation based on background subtraction and image size fitting was presented. Its simple algorithm can provide good information for real-time application. However the accuracy of this method is not very high, but it's speed is very good, we know that for real-time work speed of method is very important. This accuracy is good for most of application, but for better accuracy we can divide image to more section.

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