Vision Based Traffic Data Collection in Intelligent Transportation Systems

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Abstract: Traffic monitoring plays an important role in intelligent transportation systems. It can be used to collect real-time traffic data concerning traffic flow. Passive shadows resulted from roadside buildings or trees and active shadows caused by moving vehicles, are one of the factors that arise errors in vision based vehicle detection. In this paper, a land mark based method is proposed for vehicle detection and shadow rejection, and finally vehicle count are achieved based on the land mark detection method.

1. Introduction

Intelligent transportation systems (ITS) are the applications of recent rapid advances in information technology and telecommunications to solving transport problems. Traffic monitoring plays an important role in advanced traffic management systems (ATMS). It collects traffic data concerning traffic flow, which can be used to control traffic signals automatically and offer information on real-time traffic conditions to traffic controllers and drivers so that congestion can be avoided. Traffic data can be obtained through buried loop sensors, radar, infrared detectors and other sensors [1]. However, most of the signals acquired from these sensors have to be interpreted. On the other hand, video based systems are easily intervened by humans because images from video surveillance cameras can be viewed directly by operators. Moreover, single camera and processor can serve multiple lanes, thus, video based system spends relatively lower cost than some of the other systems. Vision based techniques are able to detect, track, classify and identify vehicles, therefore, they are widely used in intersection and freeway monitoring and control.

In vision based traffic monitoring systems, shadows make troubles for vehicle detection, especially active shadows resulted from moving vehicles. In this paper, a method based on land mark detection is proposed for vehicle detection and shadow rejection, and then vehicle count is accomplished.

2. Vehicle Detection and Count

Vehicle detection is one of key steps of vision based ITS systems, and has been accomplished via different methods. Gray-level comparison utilizes statistical variation of gray-level features for road surface and vehicle, but is sensitive to environmental change and it is almost impossible to determine the range of gray-level of vehicles due to widely varying vehicle colors. Inter-frame subtraction takes difference between two continuous frames so as to remove stationary part and get moving part within the image [2]. It is robust to environmental change, but unable to detect stationary vehicle. The effects of inter-frame subtraction are also influenced by the speed of vehicles, too low or too high speeds may result in error detection. Alternative method is background subtraction [3], which takes difference between background image and input image. In this approach, the effect of vehicle detection strongly depends on the quality of estimate background image. The background needs to be updated frequently due to changing of ambient lighting, shadow, weather, etc. Background based algorithms are very sensitive to ambient lighting conditions. Edge detection based method is another useful approach to vehicle detection, as the edge information still remains significant despite the variation of ambient lighting. However, the method will be fail if the edges of vehicle are blurred.

Although the methods mentioned above are able to detect vehicles on roads, the error caused by active shadow is still a big problem to be solved. Study [4] analyzes types and properties of shadows and tries to extract features that can distinguish vehicles from shadows. These features include gray level based true variance and truncated variance, edge based features like horizontal, vertical edge and symmetry edge, and curve based feature from front part of vehicle including vehicle head and wind shield of a vehicle etc. Based on these features, the author developed an integrated algorithm for shadow rejection, and it is claimed that the algorithm rejects over 50% of various active shadows and over 80% of the passive shadows.

In fact, the problem caused by shadows can be simply reduced by using land marks on road surface, since the land marks are invisible if they are covered by vehicle, otherwise, they still remain in images no matter whether there are shadows or not. Therefore, land marks can be used to simulate the conventional inductive loops for vision based vehicle detection.

2.1 Basic land mark based vehicle detection

To detect land marks on road surface, edge based method is utilized since edge detection is more robust to luminance change than land mark segmentation. For a gray-scale input image $\{C_{i,j}\}$, the edge intensity function of pixel $C_{i,j}$ can be represented by

$$d_{i,j} = \max\{\frac{1}{m}\sum_{y=j-1}^{j+1} w_y\left|C_{i+1,y} - C_{i-1,y}\right|, \frac{1}{m}\sum_{x=i-1}^{i+1} w_x\left|C_{x,j-1} - C_{x,j+1}\right|\}, \quad (1)$$

where w_x and w_y are coefficients depended on what operator is used for edge detection. For Sobel operators, they can be $\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$, and m=4. The binary edge image $\{E_{i,j}\}$ is obtained by

$$E_{i,j} = \begin{cases} 1, & \text{if } d_{i,j} > T \\ 0, & \text{otherwise} \end{cases}, \tag{2}$$

in which T can be chosen as a global threshold or a local threshold. In this paper, T is defined as a local threshold

$$T = \alpha + \log_{10} d_{i,j}, \tag{3}$$

where α is a constant as the lowest limit of the threshold (empirically α=23). Figs.1(a)-(b) give two input gray-scale images, in which the land marks are covered by passing vehicles, overlapped by active or passive shadow, or not covered by anything. The corresponding edge images obtained by Sobel operators are given in Figs.1(c)-(d).

After the binary edge image is gotten, the land mark region is compared with a reference image to judge whether they are matched with each other. The reference image of land mark region is shown in Fig.1(e), in which the white pixels are the edges of land marks, and the black pixels bound the ranges of land mark region of each lane. For a given binary reference image $\{R_{x,y}\}$ of lane n and binary edge image of the corresponding land mark region $\{E_{x,y}\}$, the matching is done by

$$W_n = \frac{\sum_{x,y} R_{x,y} \times E_{x,y}}{\sum_{x,y} R_{x,y}}, \quad B_n = \frac{\sum_{x,y} \overline{R}_{x,y} \times \overline{E}_{x,y}}{\sum_{x,y} \overline{R}_{x,y}}, \tag{4}$$

where $\overline{R}$ denotes the complement of R. W_n represents the ratio of number of matched white pixels to number of total white pixels in reference image of lane n, that is, the matching degree of white pixels. Likewise, B_n is the matching degree of black pixels defined as the ratio of number of matched black pixels to number of total black pixels in reference image. The final matching function is defined by

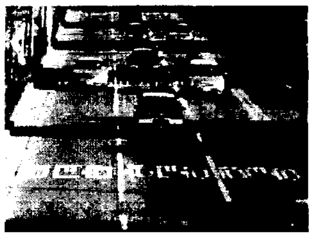
$$M_n = W_n \times B_n. \tag{5}$$

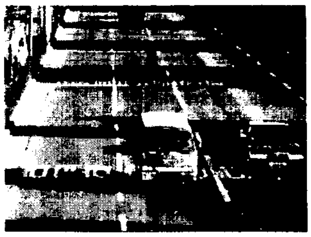
Figs.1(f)-(g) give the edge image of land mark region of the three lanes in Figs.1(a)-(b), and additionally give W_n, B_n, and M_n of each lane. It is seen that M_n of a lane in which the land marks are covered by vehicle is significantly lower than that of empty lane. Thus, the vehicle detection can be achieved by

$$V_n = \begin{cases} 1, & \text{if } M_n < Th \\ 0, & \text{otherwise} \end{cases}, \tag{6}$$

where V_n=1 indicates that there is a vehicle passing through the land mark region of lane n in current input image.

The land mark detection based method for vehicle detection is good at reducing influence of each kinds of shadows, which is a big problem for other vision based vehicle detection methods such as inter-frame subtraction and background subtraction. As we can see from Fig.1, if the land marks are not covered by vehicle, even if they are totally or partly within passive or active shadows, their M_n is still distinguished from the value calculated from land mark region covered by vehicle. And it is obvious that simpler and clearer land marks are better for raising accuracy of vehicle detection.


(a)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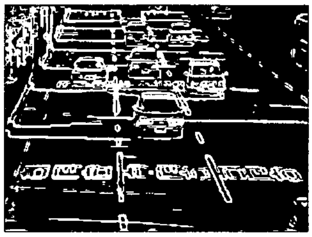
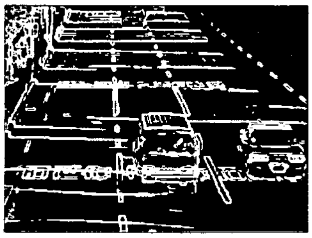

(c)


(d)


(e) Reference image of land mark edges


(f) Edges of land mark region in (c)
W_1=0.93 W_2=0.92 W_3=0.88, B_1=0.92 B_2=0.93 B_3=0.95
M_1=0.85 M_2=0.86 M_3=0.83


(g) Edges of land mark region in (d)
W_1=0.85 W_2=0.71 W_3=0.40, B_1=0.87 B_2=0.54 B_3=0.86
M_1=0.74 M_2=0.38 M_3=0.35

Fig.1 Land mark based vehicle detection.

2.2 Improved land mark based vehicle detection

It is noticed that many errors in the above basic land mark based vehicle detection arise from the slight shake of the camera, since in this case, the location of land marks in input image have small departure from that in the reference image. Usually, the departure is only within one pixel. To increase the accuracy of vehicle detection, the improved land mark based vehicle detection method is designed as follows.

1) Calculate the matching degrees of white and black pixels in case of no camera shake, land mark shift to left, shift to right, shift down, and shift up, respectively, as given in Eq.(7)-(11).

$$W_n^0 = \frac{\sum_{x,y} R_{x,y} \times E_{x,y}}{\sum_{x,y} R_{x,y}}, \quad B_n^0 = \frac{\sum_{x,y} \overline{R}_{x,y} \times \overline{E}_{x,y}}{\sum_{x,y} \overline{R}_{x,y}}, \tag{7}$$

$$W_n^1 = \frac{\sum_{x,y} R_{x,y} \times E_{x-1,y}}{\sum_{x,y} R_{x,y}}, \quad B_n^1 = \frac{\sum_{x,y} \overline{R}_{x,y} \times \overline{E}_{x-1,y}}{\sum_{x,y} \overline{R}_{x,y}}, \tag{8}$$

$$W_n^2 = \frac{\sum_{x,y} R_{x,y} \times E_{x+1,y}}{\sum_{x,y} R_{x,y}}, \quad B_n^2 = \frac{\sum_{x,y} \overline{R}_{x,y} \times \overline{E}_{x+1,y}}{\sum_{x,y} \overline{R}_{x,y}}, \tag{9}$$

$$W_n^3 = \frac{\sum_{x,y} R_{x,y} \times E_{x,y-1}}{\sum_{x,y} R_{x,y}}, \quad B_n^3 = \frac{\sum_{x,y} \bar{R}_{x,y} \times \bar{E}_{x,y-1}}{\sum_{x,y} \bar{R}_{x,y}}, \tag{10}$$

$$W_n^4 = \frac{\sum_{x,y} R_{x,y} \times E_{x,y+1}}{\sum_{x,y} R_{x,y}}, \quad B_n^4 = \frac{\sum_{x,y} \bar{R}_{x,y} \times \bar{E}_{x,y+1}}{\sum_{x,y} \bar{R}_{x,y}}, \tag{11}$$

2) Calculate the final matching function M_n.

$$M_n = \max\{W_n^0 \times B_n^0,\ W_n^1 \times B_n^1,\ W_n^2 \times B_n^2,\ W_n^3 \times B_n^3,\ W_n^4 \times B_n^4\} \tag{12}$$

3) Check whether there is a vehicle passing through the land mark region of lane n according to Eq.(6).

2.3. Vehicle count

Vehicle count is important for real-time traffic monitoring systems. It can be used to describe the load of each lane. To count the number of vehicles passing through a lane, a window is placed on the lane and a status is created for the window. For each frame, if a vehicle is detected in the window, a '1' is stored as the status of the window; otherwise, '0' is as the status. For the continuous frames, it is clear that a group of '1' corresponds to a vehicle passing through the window, while a group of '0' corresponds to the gap between two vehicles. In land mark based method, the land mark region is such kind of a window.

3. Experiments and Analysis

In the experiments, the images are grabbed from video at the rate of 2.5 frames per second. The video last about 1 hour and 26 minutes, during which the passive shadows of roadside buildings changed considerably, as shown in Fig.1 and Fig.2.

The experimental results show that the correct detection rates of the basic land mark based vehicle detection are about 92.40%, 96.89%, and 96.07% for the three lanes from left to right. The improved land mark based vehicle detection method outperforms the basic one. The correct rates of the improved land marks based vehicle detection are raised to 99.25%, 99.12%, 98.02% for the three lanes.

Table 1 gives the vehicle detection results of some different methods in details. These methods include the basic and improved land mark based methods (Basic LM and Improved LM), background subtraction method with selective updating scheme (BS_SU), and edge detection based method (Edge detection). In the table, "missed detection" means that there is vehicle present in the window but the algorithm is failed to detect it, while "false detection" corresponds to the opposite condition.

"Missed detection" in background subtraction and edge detection method mainly comes from vehicle with dark colors, especially when the vehicle is within a shadow. In this case, the luminance of vehicle is similar to that of the background, and the edges of vehicle are also not clear enough. "False detection", on the contrary, is mainly caused by active shadow made by a vehicle passing through the neighbor lane.

It is noticed that land mark based methods have lower missed detection rate than the other two methods since the land mark is invisible if a vehicle is within the land mark region. Because shadows do not influence the detection of land mark, the improved land mark based method also has lower false detection rate. In land mark based method, the false detection of a lane mainly results from vehicles that are passing through the neighbor lane but partly overlapped the current lane in input images.

Even though land mark based vehicle detection method is robust to passive and active shadows, it is poor in detecting motorcycles, because they cover less part of land marks when passing through the land mark region. Fig.2(a) shows such an examples, in which the pair of "1" and "0" under the corresponding frame is the detection results V_n and the one marked by "*" indicates an incorrect detection.

Vehicles that are changing the lane also make troubles for the proposed method, since they affect land mark regions of two lanes when they are driven at the middle of the two lanes, as shown in Fig.2(b).

Big vehicles such as buses, trucks may cause the similar problem if they overlap other lane in the input image. It is noticed that big vehicles driven at the left lane in the test images usually do not cause errors, by contrast, big vehicles at the middle lane bring errors for vehicle detection of the right lane, as shown in Fig.2(c) and (d). That is why the correct rate of the right lane is the lowest when land mark based method is used for vehicle detection. In fact, this is mainly due to the angle of view of the camera, which was mounted on an overbridge with about 6 meters high over the road. It is realized that the location of camera is critical to effective operation of the video based vehicle detector. A solution to reduce the errors caused by big vehicles is to mount camera at a higher position. However, the errors that arise from some vehicle overlap other ones in image, is inherent problem of vision based vehicle detection methods.

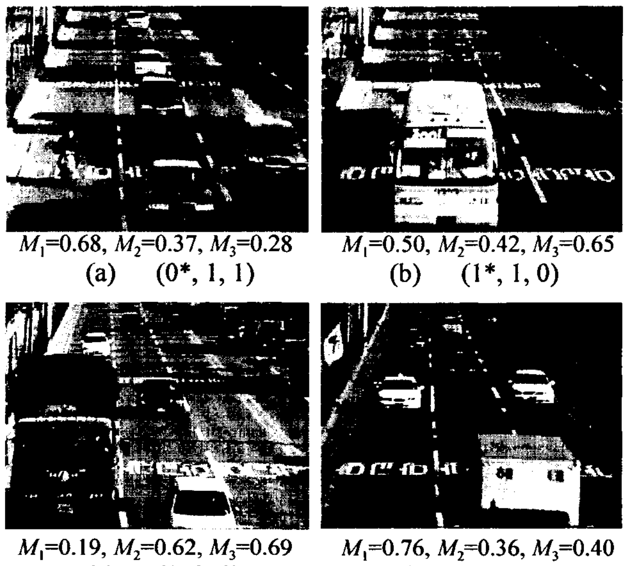


Fig.2 Some test frames and the detection results.

Table 1. Comparison of vehicle detection

Methods \ Results	Left lane			Middle lane			Right lane		
	Missed detection rate	False detection rate	Correct rate	Missed detection rate	False detection rate	Correct rate	Missed detection rate	False detection rate	Correct rate
Basic LM	0.18%	7.41%	92.40%	0.34%	2.77%	96.89%	1.31%	2.63%	96.07%
Improved LM	0.41%	0.34%	99.25%	0.42%	0.45%	99.12%	1.64%	0.34%	98.02%
BS_SU	2.64%	2.47%	94.89%	4.57%	2.14%	93.29%	2.33%	1.85%	95.82%
Edge detection	1.52%	0.40%	98.08%	2.26%	0.95%	96.79%	2.59%	1.19%	96.23%

Fig.3 gives the results of vehicle count by using the improved land mark based method, background subtraction and edge detection method compared with the results of manual count. The three figures correspond to the three lanes shown in Fig.1 and Fig.2. The horizontal axis of the figures represents the time, the unit of which is minute, while the vertical axis is the number of passing vehicles within every 2 minutes. The solid and dotted lines in Fig.3 correspond to the result of manual count and improved land mark based method, respectively. The meanings of symbols are given under the figure.

Generally speak, vehicle count under light traffic condition is more accurate than heavy traffic, since several vehicles may pass through a window continuously under heavy traffic condition, that is, there is no '0' status between two vehicles thus the following vehicle is missed in vehicle count. If the frame acquire rate is high enough, this problem will be reduced. In the experiments, it is shown that land mark based method is good at shadow rejection.

4. Conclusion

In this paper, a land mark detection based method is proposed for vehicle detection and shadow rejection, since the land marks are invisible if they are covered by vehicle, otherwise, they still remain in images no matter whether there are shadows or not. Based on the vehicle detection method, vehicle count is achieved so that traffic data concerning traffic flow is obtained to describe the load of each lane.

References

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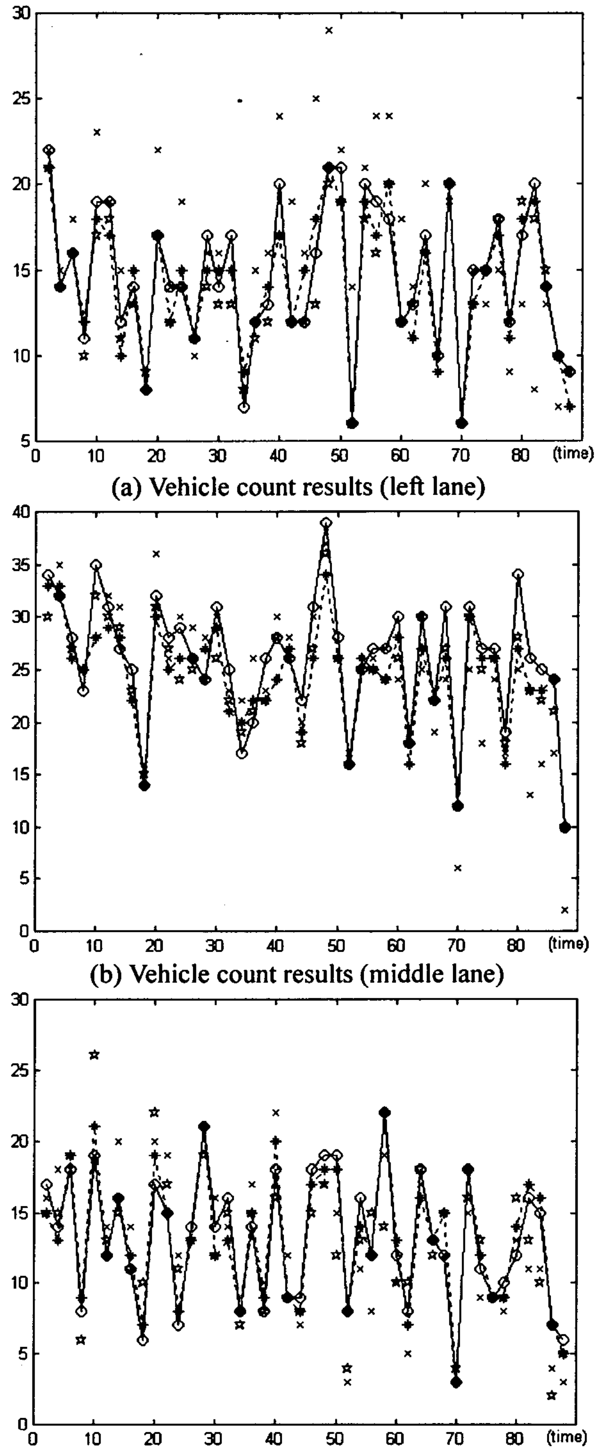

(a) Vehicle count results (left lane)

(b) Vehicle count results (middle lane)

(c) Vehicle count results (right lane)

Note: '- -✳- -' Improved LM; '—O—' Manual; '×' BS_SU; '☆' Edge detection;

Fig.3 Comparison of vehicle count.