# A PRACTICAL AND EFFECTIVE INTELLIGENT TRAFFIC COUNTING METHOD 

Huajun Song, Guangbing Zhou, Jianle Zhao, Yuxing Wu and Peng Ren*<br>College of Information and Control Engineering<br>China University of Petroleum (East China)<br>No. 66, Changjiang West Road, Qingdao 266580, P. R. China<br>*Corresponding author: pengren@upc.edu.cn

Received January 2017; accepted April 2017


#### Abstract

In traffic flow detection, there are a lot of special conditions, such as heavy traffic flow, no movement of vehicles, small vehicles spacing, and illumination changing, which impact detection precision. In order to overcome these conditions, a practical and effective integrated method is proposed. It takes frame difference values as background update judging conditions. HSV (Hue, Saturation, Value) features are used to clean up shadows. Hough transform is used to correct rotations of video frames. Background difference value method is applied to getting vehicles and counting it. Experimental results show that the proposed method achieves high traffic flow detection accuracy of 92\% and can be applied in actual project.


Keywords: Traffic flow detection, Gaussian background modeling, Frame different value method, Hough transformation

1. Introduction. Main applications of computer vision include object recognition, image registration [1], motion detection and tracking [2]. Traffic flow detection also has important applications in intelligent transportation system (ITS). It mainly uses image processing techniques: processing image obtained from cameras installed on the traffic intersections or high-buildings. This method does not affect the normal traffic and has low cost and easiness to maintain, but its accuracy is low. To improve the accuracy of detection, this paper designs a high-performance traffic flow detection algorithm based on image processing.

Traffic flow computing core algorithm mainly includes frame difference values method, background difference value method and optical flow method, etc. However, because of the complex background, heavy traffic and many other factors, accuracy of detection has been limited under those factors or conditions. A background difference method for detecting moving vehicles is proposed in [3], which is suitable for different viewing angles and light changes with constantly updated background. However, the algorithm has low detection accuracy when the moving vehicle stopped, because the stopped vehicle will be regarded as a part of the background. Method in [4] put forward a detection algorithm based on the illumination changes. This algorithm will not be affected by vehicle stop, which utilizes the characteristics of the vehicle edge and lights information under different light conditions to extract the information of target vehicle. However, it requires the angle between cameras and light should not be too large, which actually changes with external conditions, so the algorithm is not able to meet the actual requirements. Method in [5] proposed a kind of algorithm that combines background difference and edge detection, which defines the scan width and uses the local threshold segmentation according to the lane line. This method can be applied to most kinds of traffic conditions with high precision. However, the algorithm is not suitable for traffic flow detection because its dependency on the lane designated and the vehicle often do not follow a given lane. Method combining shadow
elimination with optical flow is put forward in [6], which eliminates the influence of shadow very well and has good accuracy when the traffic is not heavy. However, when the traffic is heavy, especially vehicle occlusion occurs, the algorithm is not able to distinguish single car and detect accurately the number of vehicles.

In order to overcome the above disadvantages, this paper proposes a new traffic flow detection algorithm which combines frame difference values and background difference value method, in which frame difference values are taken as judging conditions of background update. It solved the problem of the influence to the background from light change and the problem that the frame difference cannot detect stopped vehicles. The proposed method will be described in the following section in detail.
2. New Background Update Strategy. The mixture Gaussian to build background model [7] is used which extracts pixels from the video frame according to a certain rule and extracts background information based on the Gaussian distribution. Due to the change of background with the sunlight or shadow by buildings, background update strategy is important for extracting vehicles [8].

Detect the vehicles between adjacent frames with difference value method [9]. Given that $f^{(t)}$ and $f^{(t+1)}$ are two adjacent frames in the video sequence, the inter-frame difference image is $f^{(k)}=\left|f^{(t)}-f^{(t+1)}\right|$. The total sum of pixel values which were obtained by the frame difference method is significantly less than that obtained by background difference method, so this paper uses this character to detect traffic conditions, and then update the background.

Acquire information of traffic congestion by the contrast of the frame difference method and the background difference method, and then decide whether to update background or not. Given that the background difference result is $f^{(b)}$, and the frame difference result is $f^{(k)}$, then the judgment is as follows:

$$
\begin{equation*}
\theta=\frac{\sum f^{(b)}(i, j)}{\sum f^{(k)}(i, j)} \tag{1}
\end{equation*}
$$

In this equation, $\sum f^{(b)}(i, j)$ represents the sum of each pixel brightness after background difference processing, and $\sum f^{(k)}(i, j)$ represents the sum of each pixel brightness after frame difference processing. When traffic jams do not occur in video frames, difference between $\sum f^{(b)}(i, j)$ and $\sum f^{(k)}(i, j)$ is micro, so the value of $\theta$ is small. When traffic jams do occur in video frames, frame difference will not demonstrate the stopped cars, so the value of $\sum f^{(k)}(i, j)$ is relatively small, which leads to a greater value of $\theta$ than that when traffic jams do not occur. Through a large number of experimental data, we found that when $\theta \leq 3$, the traffic situation is good; when $3<\theta \leq 30$, the traffic situation is relatively poor and traffic jams occur; when $\theta>30$, most cars are in the stationary state. So, we can determine whether to update the background through Equation (1).

Figure 1 shows the truncated picture of the video at four different time: (a) contains a small amount of moving vehicles; it begins clogging in (b), while most vehicles move slowly, and some even stop; in (c), most vehicles stop in lane; almost all the vehicles keep still in (d). Results calculated by Equation (1) are shown in Table 1.

Table 1. Analysis of traffic congestion condition

| Screenshot <br> number | Ratio obtained <br> by Equation (1) | Traffic condition | Whether update <br> background |
| :---: | :---: | :---: | :---: |
| (a) | 1 | unimpeded | Yes |
| (b) | 6 | worse | No |
| (c) | 28 | congestion | No |
| (d) | 40 | congestion | No |



Figure 1. Analysis of experimental results of traffic congestion judgment

From the experimental results this method can effectively solve the mistaken update of the background when vehicles stop moving.
3. Proposed Vehicle Rectangular Computing Method. In order to track and count vehicles in the segmented image, the method that calculates the minimum external rectangle of the vehicle is used [10], and then the vehicles can be expressed by rectangle. Because the lane is tilted, the Hough transform is first used to rotate the image, and then real-time location of vehicles can be calibrated by rectangle frame [11]. The algorithm steps are as follows:
a) Rotate the segmented image using Hough transform;
b) Select the upper-left corner of the processing region as the starting point, and then begin to traverse each pixel in the selected region from the starting point;
c) Find the first pixel whose value is 0 , take this pixel as the head node to establish a linked list, and mark the list as 0 ;
d) Starting with this point, check pixels from the three directions: upper, lower and right. Add the 0 pixel points to the linked list marked 0 ;
e) Regard the 0 pixel points in the three directions as the starting point respectively, and repeat step d), until to the lower right corner of the selected area;
f) If a pixel valued 0 is not adjcent to the last pexel of any previous linked lists, then generate a new linked list taking this point as the head node;
g) After searching all pixels, calculate the minimum external rectangle of every linked list: for the coordinate of the upper-left corner in the rectangular, its $x$-coordinate is the smallest $x$ of all the pixels $(x, y)$, and $y$-coordinate is the smallest $y$ of all the pixels $(x, y)$.

Similarly, for the coordinate of the lower-right corner, its $x$-coordinate is the largest $x$ of all the pixels $(x, y)$, and $y$-coordinate is the largest $y$ of all the pixels $(x, y)$;
h) Ignore the rectangular whose size is not in conformity with the vehicle obviously, and then the rectangular obtained is exterior rectangle of vehicle.
4. Background Update Traffic Detection Algorithm. From Figure 2, the process of the algorithm is as follows:
(a) Accumulate the video frames read by the system to calculate the time parameter. Process video frames with Hough transform to obtain tilt angle information of road;
(b) Preprocess the video frames mainly about cleaning up dark shadow of the video during the day with shadow elimination algorithm [12] which is based on HSV feature [13];
(c) Obtain background information by Gaussian background modeling method, and calculate the gray level difference between the current frame and the model background images. At the same time, process input video frames with difference value method;
(d) Compare the differences between the result of background difference method and frame difference method, and then determine whether to update the background or not;
(e) Rotate the images after the background difference to make the road in horizontal direction;
(f) Adaptive threshold segmentation method is used to obtain vehicles' binary information;
(g) Traverse the binary image after threshold segmentation [13,14]. Calculate the minimum external rectangle of vehicles in the image and count vehicles.


Figure 2. The overall flow chart of traffic detection algorithm
5. Experimental Results. The proposed method runs in high speed processor hardware system which uses TMS320DM6446 as core processor, so it is difficult to compare the performance among different methods. On the basis of quantization and analysis of the actual test environment, this paper made an experimental comparison among traditional background modeling method [7], frame difference values [9] and synthesis method proposed by this paper. This experiment used the data of Qingdao expressway surveillance video at 17 o'clock to 19 o'clock on a spring day to test those methods. Around 80 minutes (i.e., at 18:20), traffic flow reached its peak and light intensity was weakening with time.


Figure 3. The error rate of traffic flow calculation
Table 2. The overall accuracy of the traffic flow counting

|  | Background modeling method | Frame difference values | Proposed method |
| :--- | :---: | :---: | :---: |
| Accuracy | $64 \%$ | $71 \%$ | $\mathbf{9 2 \%}$ |

Figure 3 showed the error rate obtained by comparing the traffic flow calculated and the actual in every minute.
Figure 3 illustrates that the accuracy of the background modeling method will decline when the number of cars changes seriously in that it is more complex and difficult to establish background model accurately when the traffic flow changes.

Frame difference values method and background modeling method have certain limitations in practical application. The proposed method combines the advantages of frame difference values and background modeling method, and makes up for the inadequacy of the two methods through integration. This method has stronger robustness towards the changes of traffic flow and light intensity and obtained high precise results of traffic flow when light intensity was weakening in the evening and traffic flow changed obviously.

Throughout the two hours, the precision (accuracy) of the general flow calculation is shown in Table 2.

As can be seen from Table 2, the comprehensive method proposed by this paper overcomes the deficiency of frame difference values and background modeling method, and obtained satisfactory results.

On the basis of quantitative analysis above, visual experimental results of traffic detection are given as follows.

Figure 4 is the test results of traffic flow during the day. Big rectangle represents the detection area, and small rectangle represents the test vehicles. As can be seen the road direction becomes horizontal after Hough transform, and the influence of shadow was


Figure 4. Detection effect during the day


Figure 5. Detection effect at night
eliminated well. In Figure 4, there are more vehicles in video frames shown in the two picture in the last row, and many vehicles moving slow even stop. However, the number of vehicles can still be correctly detected.

Figure 5 is the test results of traffic flow at night. Figure 5 showed that the number of vehicles in the selected area is detected correctly.
6. Conclusions. In order to improve the problem of failure detection of the background modeling method when vehicles stop, a method combining with frame difference to determine the conditions of background update was proposed. Traffic detection of the appointed road was realized by using the Hough transform, HSV shadow elimination and adaptive threshold segmentation algorithm. Experimental results show that the proposed method achieves high traffic flow detection accuracy and exhibits robustness to different external factors. However, the algorithm is more complex, so it cannot meet real-time processing requirement under the high resolution camera. So, the algorithm will be optimized to achieve the real-time traffic detection.

Acknowledgment. This work is partially supported by the National Natural Science Foundation of China (No. 61305012) and Science and Technology Planning Project of Jilin Province 20140101066JC. The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

## REFERENCES

[1] H. Song and P. Qiu, A parametric intensity-based 3D image registration method for magnetic resonance imaging, Signal Image \& Video Processing, pp.1-8, 2016.
[2] H. Song, B. Xiao, H. U. Qinzhen et al., Integrating local binary patterns into normalized moment of inertia for updating tracking templates, Chinese Journal of Electronics, vol.25, no.4, pp.706-710, 2016.
[3] N. A. Mandellos, I. Keramitsoglou et al., A background subtraction algorithm for detecting and tracking vehicles, Expert Systems with Applications, vol.38, no.3, pp.1619-1631, 2011.
[4] Y. M. Chan, S. S. Huang et al., Vehicle detection and tracking under various lighting conditions using a particle filter, Intelligent Transport Systems, vol.6, no.1, pp.1-8, 2012.
[5] X. Pan, Y. Guo et al., Traffic surveillance system for vehicle flow detection, The 2nd International Conference on Computer Modeling and Simulation, 2010.
[6] Z. Zhang, Y. Hou, Y. Wang and J. Qin, A traffic flow detection system combining optical flow and shadow removal, Intelligent Visual Surveillance (IVS), 2011.
[7] D. Gutchess, M. Trajkovic, E. Kohen-Solal, D. Lyons and A. Jain, A background model initialization algorithm for video surveillance, Proc. of the 8th International Conference on Computer Vision, vol.12, pp.733-740, 2001.
[8] K. Kim, T. H. Chalidabhongse, D. Harwood et al., Real-time foreground-background segmentation using codebook model, Real-Time Imaging, vol.11, no.3, pp.172-185, 2005.
[9] Z. Zivkovic and F. Van der Hijden, Efficient adaptive density estimation per image pixel for the task of background subtraction, Pattern Recognition Letters, vol.55, no.5, pp.773-780, 2002.
[10] N. Herodotou, K. N. Plataniotis et al., A color segmentation scheme for object-based video coding, Proc. of the IEEE Symposium on Advances in Dzgital Fzltering and Signal Processing, pp.25-29, 1998.
[11] S. Ye, Research of the Detection and Tracking of Cars in Intelligent Transportation Systems, Southeast University, 2009.
[12] R. Cucchiara et al. Improving shadow suppression in moving object detection with HSV color information, IEEE Intelligent Transportation Systems Conference Proceedings, 2001.
[13] Y. Li, R. Zhu, L. Mi, Y. Cao and D. Yao, An improved acute lymphoblastic leukemia image segmentation scheme based on HSV color space, ICIC Express Letters, Part B: Applications, vol.7, no.9, pp.1983-1989, 2016.
[14] P. S. Mukherjee and P. Qiu, Image denoising by a local clustering framework, Journal of Computational 8 Graphical Statistics, vol.24, no.1, pp.254-273, 2015.

