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Vehicle Flow Counting System Based on Traffic Surveillance Video

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Abstract. With the rapid development of intelligent traffic surveillance systems, traffic monitoring has become automatic and intelligent. Traffic flow detection is an important part of Intelligent Transportation System (ITS), and it plays an important role in traffic management and monitoring. In this paper, we propose and implement a traffic surveillance system for vehicle flow detection and counting. The system we proposed consists of three parts: target detection, target tracking and target counting. Based on background modeling, we detect the foreground target and Mean-shift color histogram matching algorithm has been adopted to track the target. Then we set the detection line to count the target in the region of interest (ROI). The experiment results show that our proposed system has good performance and high accuracy in real traffic video.

Keywords: Mean-shift algorithm, target detection, target tracking, vehicle flow, virtual detection line

1 Introduction

With the rapid development of economic, people's living standards have been improved and the number of cars has gradually increased. The large number cars have caused traffic congestion, which not only waste people's time but also increases the probability of traffic accidents. Many cities have taken measures to build three-dimensional traffic such as overpasses and underpass tunnels, or to increase the number of lanes to wide roads. Although the traffic congestion problem has been alleviated to some extent, its growth rate still cannot match the growth rate of the car. Therefore, it's important to accelerate the establishment of intelligent transportation, which is conducive to the management of urban transportation.

Intelligent video surveillance is an emerging application direction in the field of computer vision. It involves many research fields such as image processing, image analysis, machine vision, pattern recognition, artificial intelligence, etc. It is an interdisciplinary and challenging subjects [1-3]. The intelligent video surveillance system uses computer vision technology to process the video signals collected by the camera. This system can locate, identify and track targets by automatically analyzing sequence images without human intervention and improve the intelligence level of video surveillance systems [4-5].

The application of intelligent video surveillance technology in social life is more and more extensive, and the popularization of intelligent products has also brought us great convenience, especially in

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security system. We can master the real-time traffic conditions through the statistics of traffic flow. According to the statistics, we can take measures in advance to prevent the occurrence of dangerous events and create a more comfortable and convenient living space for the society. Counting on vehicle flow has strong practical significance and it is also the focus of research [6-8]. In this paper, we proposed a vehicle flow counting system, which can detect and track the vehicle to obtain the traffic flow statistics.

2 Related Work

There are many traditional methods for achieving traffic flow detection. The air duct inspection technology sets a hollow plastic pipe containing a counter on the road, and the counter is counted when the vehicle passes through the plastic pipe. Magnetic induction detection technology detects vehicles by electromagnetic induction and counts them. Ultrasonic and infrared detection can also be used to complete vehicle counting. In the 21st century, with the development of computer technology, digital image processing, artificial intelligence and other technologies has occupied an increasingly important position in traffic information monitoring. The most important part of the traffic flow counting system is target detection and target tracking. Many scholars spend a lot of time researching in them.

The idea of traffic counting system is to set a fixed region as a virtual detection line in the video image, and then count the traffic flow in this region. The first step is detecting the foreground target. Kyungnam et al. proposed the Code-Book background model [9], each pixel is described by a code-book, which is suitable for motion scene modeling. Another target detection method based on machine learning which does not need to establish a background model of the video. It directly detects the target from the original video. For example, DPM (Deformable Part Model), which considers the target to be composed of multiple components and uses the relationship between the components to describe the target [10]. The Over Feat [11] method uses a multi-scale sliding window to extract target features and uses convolution neural networks for target classification and detection.

An important part of the traffic flow counting system is the target tracking, which is to match the same target in different image frames. There are many researches on target tracking algorithms. Comaniciu et al. proposed a Mean-shift-based tracking method [12], which uses the histogram of the target of interest as the search basis. In the next frame, the Mean-shift algorithm is used to obtain the maximum probability density of the feature which is the matched target. Bouguet proposed a method based on optical flow method [13], which first detects feature points in the image and then uses block matching to find the new position of these feature points in the next frame.

In this paper, we propose and implement a smart video vehicle flow counting system. The organization of this paper is as follows: The first part introduces the basic information of traffic flow counting system. The second part shows the related work of this subject. The framework of our proposed system is shown in third part. We explain how the modules of our system are realized in detail in forth part and then we test the accuracy of our system through experimenting in different situations. Finally we draw a conclusion and make discussion about future work.

3 System Diagram

This system realizes the functions of automatically detecting, tracking and counting multiple targets in the video sample in a complex environment captured by a fixed camera. First, we detect the foreground target in the region of interest. Then the foreground target in the core region is tracked. Finally we can obtain the vehicle flow. The block diagram of our system is shown in Fig. 1.

4 Traffic Flow Counting

In this section, we will illustrate our traffic flow counting method in detail, mainly including foreground object detection, target tracking and traffic flow counting method.

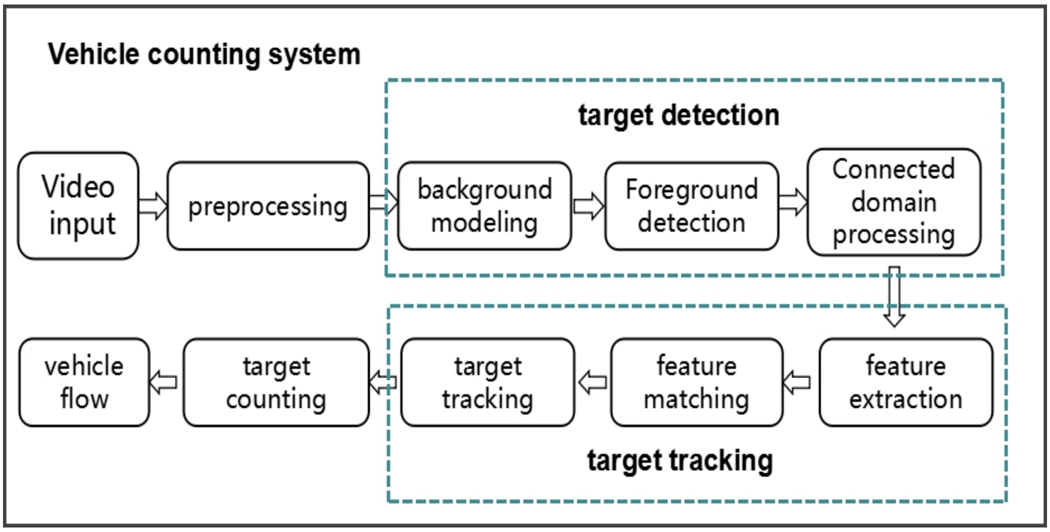

Fig. 1. System block diagram

4.1 Foreground Object Detection

The purpose of foreground target detection is to distinguish foreground information from background information. First, we modeled the background image of the image frame sequence. Then we compare the frame to be processed with the established background information which has been gained in background model, after that a binary foreground image can be obtained. Finally, we use the rectangle to mark the foreground target and split it from the image to get the target template.

In our system, we consider the two-frame difference of three consecutive frames to judge the foreground pixel and the background pixel and obtain the binary image of the intermediate frame.

We assume that the three consecutive frames are I_{k-1}, I_k and I_{k+1}, then we use the following formula to calculate the difference image between two adjacent frames:

$$d_{(m,m-1)}[x,y] = \left| I_m[x,y] - I_{m-1}[x,y] \right| . \tag{1}$$

where $I_m[x,y]$ represents the pixel value at the point (x, y) in the frame m, $d_{(m,m-1)}[x,y]$ represents the pixel value of difference image between the frame m-1 and frame m at the point (x, y).

Then, we conduct binary operations on the difference image according to the formula as shown in (2) to obtain a binary image.

$$b_{(m,m-1)}[x,y] = \begin{cases} 1, d_{(m,m-1)}[x,y] \geq T \\ 0, \text{others} \end{cases} \tag{2}$$

Where $b_{(m,m-1)}[x,y]$ represents the pixel value of binary image at the point (x, y) in the frame m-1 and frame m. T is a threshold value given by us, which is used to determine whether the current pixel is foreground or background.

The binary image obtained by the above method contains noise and small cracks, so we can use the morphological opening and closing operation and delete the small connected domain to obtain a better result. Fig. 2 shows the segmentation results for vehicles..

4.2 Target Tracking

The foreground target tracking is to find the target in the region of interest (ROI) of each sequence of image sequences and track its motion trajectory. In our system, we use the color histogram of RGB [14] to describe the target feature, and then establish the target template. In the tracking process, the Mean-shift prediction algorithm [15] is adopted to search for the foreground target to be tracked. The steps of the tracking algorithm are shown in Fig. 3.

(a) picture is the binary image (b)one is segmentation result for vehicles

Fig. 2. The segmentation results

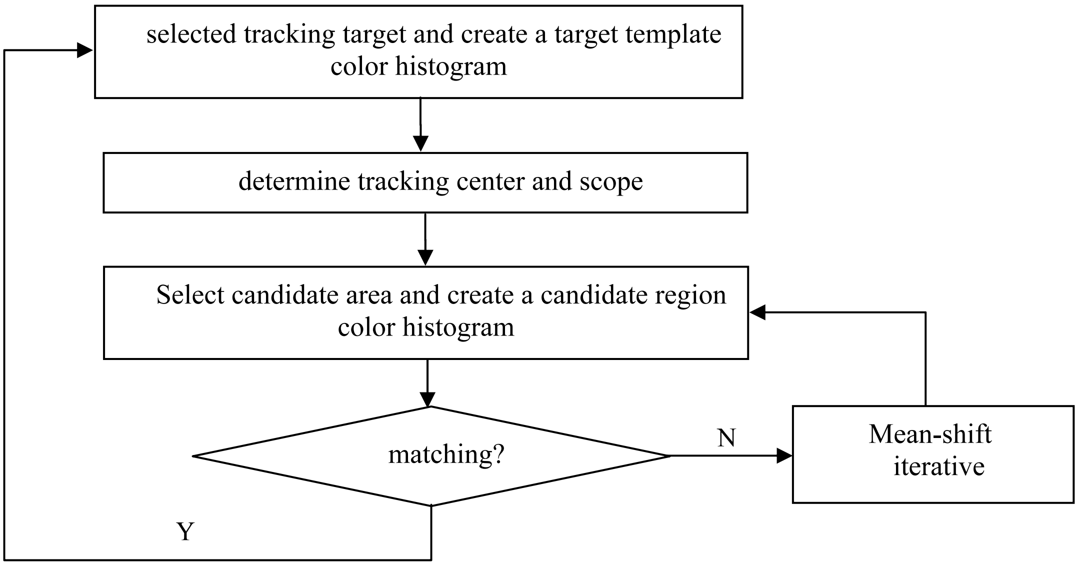

Fig. 3. the steps of tracking algorithm

We consider that the tracking is completed when the template matching satisfies a threshold or the number of iterations reaches a maximum. The motion trajectory can be drawn through the target mass center changing records in the video sequence. We implement single-target and multiple-target tracking. When tracking multiple targets, not all the detected foreground targets are tracked at the same time. Instead, we track multiple targets in turn based on the connected domain number which is set during the target detection phase. Fig. 4. shows the target tracking results.

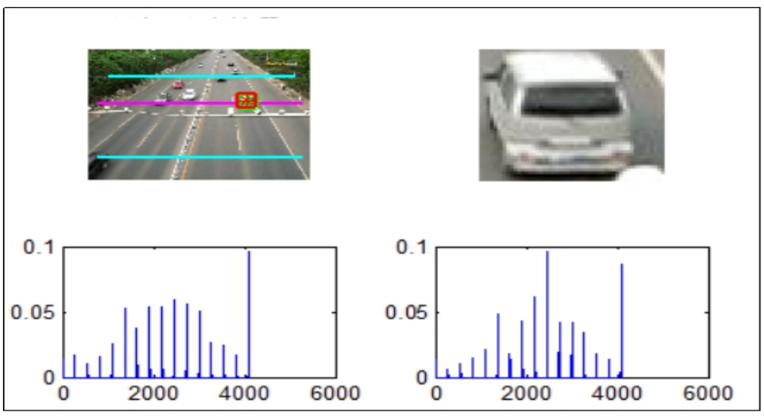

Fig. 4. The picture of upper left is target tracking result, the upper right one is target template, the bottom left one is the histogram of target template, the bottom right one is the histogram of candidate region

4.3 Target Counting

The system uses the method of setting a virtual detection line to perform target traffic statistics in the region of interest. Extracting position information and feature information of the foreground target of the current frame in the region of interest, and using the extracted color feature to match target in the next frame. Finally, as shown in Fig. 5, we compare the center of the detected target region with the center of the candidate region which is tracked by the feature information. If there is a cross-line phenomenon between the positions of the two centers, the counting is performed. We use the following criteria to count targets:

$$\begin{cases} Ax + By + c = 0 \\ Ax_0 + By_0 + c = t_0 \\ Ax_1 + By_1 + c = t_1 \\ K = t_0 t_1 \end{cases} \tag{3}$$

The first equation indicates the position of the test line. The second and third equation indicates a target in different position at two moments.

We gain the vehicle flow based on the value k, if the value k is less than zero, it means that the detected target has passed the detection line, and we increment the counter by one. If the value k is greater than zero, no counting is performed.

We can also judge the direction of motion of the target based on the values of t_0 and t_1. If we define t_0 to be greater than zero and t_1 is less than zero indicate that the target is the entry region. Then t_0 is less than zero and t_1 is greater than zero indicates that the target left the region. We can count the number of targets in a certain region based on that criteria.

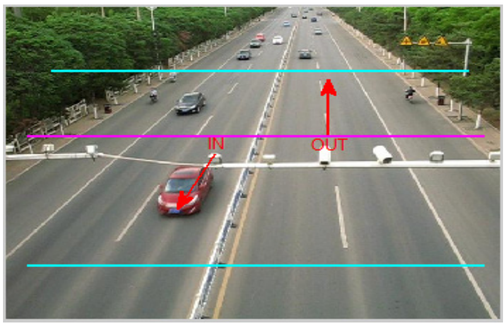

Fig. 5. Virtual detection line

5 Experiment Results

5.1 Experiment Data

We use the software MATLAB2014a to implement our proposed scheme. The data used in the experiment are the traffic road video taken by the camera. We digitize the video data. In our experiment, the digitization was 30 frames per second. Fig. 6 shows the frame images that we have cut.

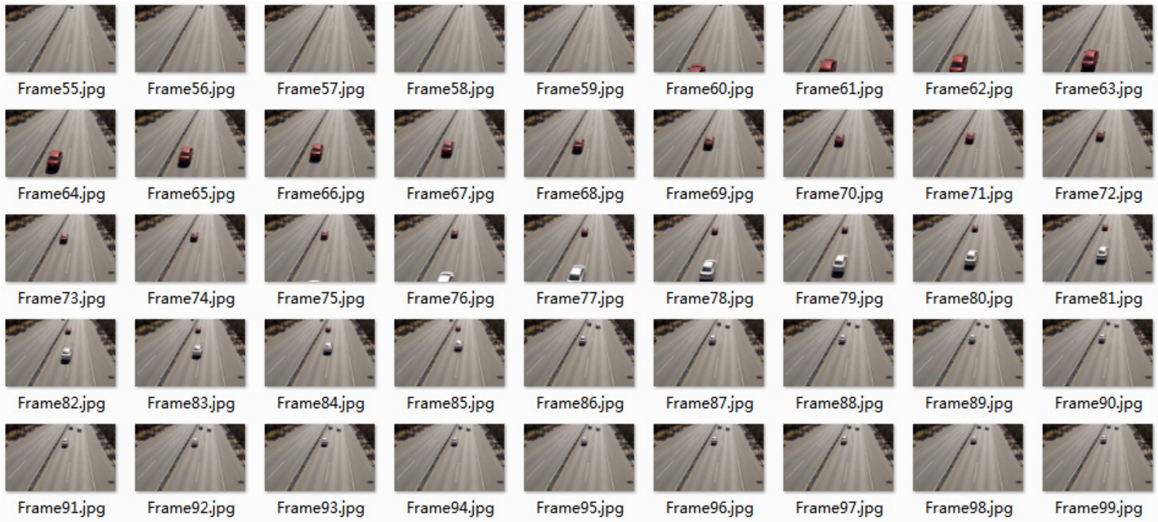

Fig. 6. Frame images cutting from video

5.2 Results

We select twenty consecutive frames from any position in the video sequence, and Fig. 7 shows the detected values and tracking values of the centroid positions of the same target.

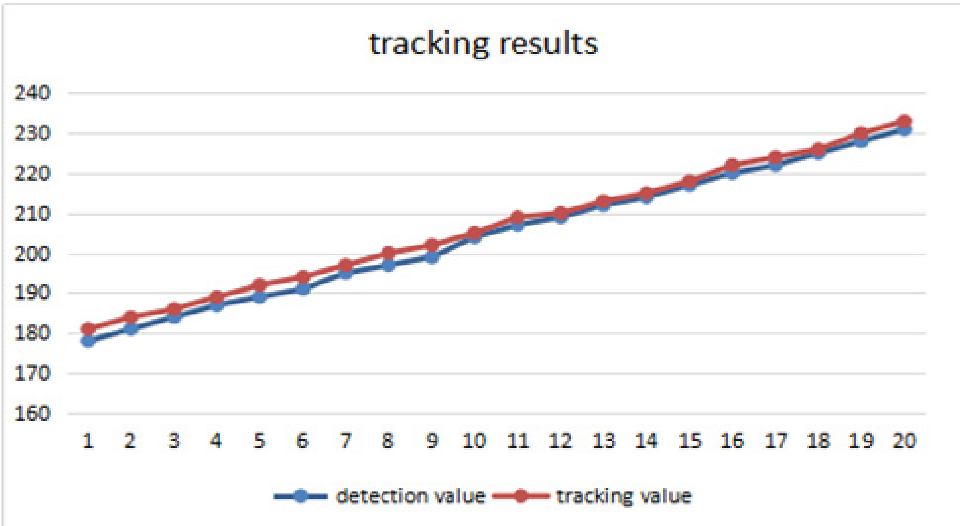

Fig. 7. The detection and tracking value of the same target

As shown in Fig.7, the value of target tracking is basically consistent with the detected, but there is still some differences. The main reason is that the target position change between adjacent frames is small, especially for targets with slower motion. In order to get more accurate results, we adopt the following two strategies: (1) we judge whether there is a cross-line phenomenon between the frame k and the frame k+N, instead of the adjacent two frames. The value of N is set in advance according to the application environment. (2) If a target has multiple cross-overs in successive frames, the counter counts only once.

We use the above two criteria to calculate traffic flow, and Fig. 8 is an example of the result of the traffic flow statistics. In this example, we set a test line perpendicular to the direction of travel of the vehicle. If the vehicle passes this test line, the counter is incremented and we show the number of vehicles in the image.

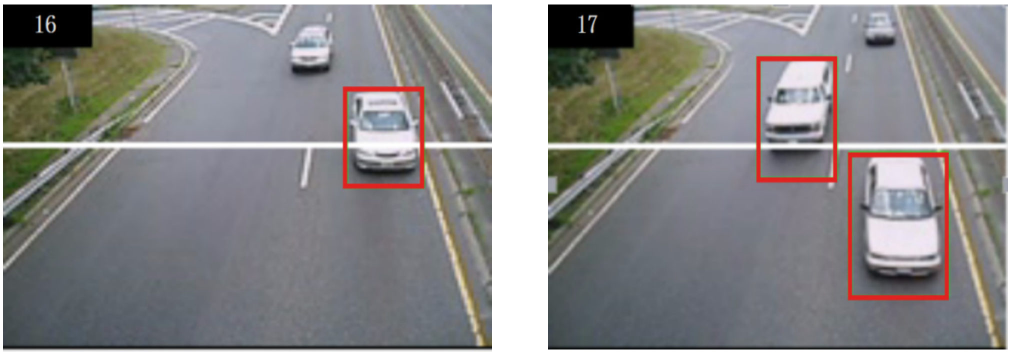

Fig. 8. An example of vehicle counting result

We selected the videos in four different scenes to test the accuracy of our proposed system, for example single or double lane, downtown or suburban lane. Table 1 shows the accuracy of our method.

Table 1. Accuracy of different types of road

Type of road	Single lane in downtown	Double lane in downtown	Single lane in suburban	Double lane in suburban
Rate of accuracy	94%	93%	96%	94%

From the data in the Table 1, we can see that the overall performance of our proposed system is good, but it also exists some difference. The urban roads have lower accuracy than the suburban roads, and the double lanes have lower accuracy than the single lanes. That may because that the traffic flow in the urban area is larger than that in the suburbs, and there are more undetected and not tracked targets.

6 Conclusion

In this paper, we propose a vehicle and person flow detection system based on traffic monitoring video. After the background modeling and target detection, we adopt the mean-shift algorithm to track targets. Then, we set up the detection line to complete the counting of vehicles in the area of interest.

The experimental results show that our proposed system has a good performance. However, there are some limitations, for example we have not considered the effects of different weather conditions and day or night situation on the detection and counting of the system's targets. In the future, we will do more research on target detection and track and apply them in more scenarios.

Acknowledgements

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