A New Algorithm For Background Extraction Under Video Surveillance

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Abstract—**Path motion object detection based on video is a fundamental part of intelligent transportation systems, In the aspect of background extraction, this paper compared all existing theories and algorithms, aimed at specific objects (city expressways or high-speed Road), and combined with the virtual loop set method. This paper proposed an extraction and updating algorithm based on the sub-segmentations of invariant background, which greatly increased the time efficiency of the background extraction. It achieved great results of accuracy and real-time of this algorithm under background extraction.**

Keywords-Intelligent Transport; Video Surveillance; Background extraction

I. INTRODUCTION

Image processing technology has been widely used in intelligent video surveillance system. Intelligent transport system uses a large quantity of video surveillance technology. Video-based moving object detection is a basic part of intelligent transport, which provides foundation for analysis of automatic traffic and vehicle information. The most commonly used and most effective moving object detection method is Background Subtraction algorithm, and background extraction is the key step of background subtraction. Background extraction has a direct impact on the accuracy of motion detection, and relates to the reliability of further analysis of the video image information.

Currently, there are many background extraction algorithms. There are timeline-based filtering methods, such as mean method, median method, Surendra method [1]. There are statistical model-based methods, such as single Gaussian model, mixture of Gaussian model, MoG [2, 3], non-parametric model [4,5]and so on. There are other methods such as Kalman filter (KF) based on predicted Method. These methods were applied to various situations of vehicle detection and made some achievements. But there is a big difference in background accuracy extracted by various algorithms under different circumstances because of moving objects on the road usually have more complex environment. The applicability of various algorithms also need further study. This paper provided a new background extraction algorithm based on the existing algorithms[6-11]—sub-segmentations background extraction algorithm based on the invariant.

II. ALGORITHM

Assuming that the background of a regionwas non-mutinous and continuous in a short time in the case of less traffic. We could get these background pixels within the region continuous basis of this invariance. This chapter proposed sub-segmentations background extraction algorithm based on the invariant according to this hypothesis.

Set interest region of image, namely, divided the image segmentation, then the image was divided into n segmentations and each piece of segmentation was independent of each other. Then seek their background and combine them into the final background image. Sub-segmentation size should be reasonable. The segmentation area can not be too small; otherwise it affected the efficiency of extraction of the background. Similarly, the segmentation area can not be too large; otherwise it wass too hard to make the background. The procedures of sub-segmentations background extraction algorithm based on the invariant are as follows.

A. Determine the image feature parameter.

There were several common ways to describe the image texture features:

Average gray value:

$$\mu = \sum_{i=0}^{L-1} iP(i) \tag{1}$$

Gray variance:

$$\sigma^2 = \sum_{i=0}^{L-1} (i-\mu)^2 P(i) \tag{2}$$

In formula (1), (2), P (i) was the probability of different gray level series. L was the gray level. When mean and variance used as parameters, it needed Small amount of computation and achieved easily. So the background initialization algorithm mainly used these two parameters. But μ and σ^2 often affected less on the overall image similarity judgments, so overall similarity judgments were introduced in as auxiliary characteristic parameters.

$$\xi = \frac{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} I_{t-1}(m,n) I_t(m,n)}{\sqrt{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}[I_{t-1}(m,n)]^2}\sqrt{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}[I_t(m,n)]^2}} \tag{3}$$

In formula (3), ξ was Similarity parameter, $I_{t-1}(m,n)$ 、 $I_t(m,n)$ were the pixel values of The previous frame and current frame. ξ represents that when $I_{t-1}(m,n)$ coincides with $I_t(m,n)$ completely, ξ equals one.

We assume that the signal or noise obeys to a normal distribution in previous paragraph, so the second-order statistics can be used to extract information. But the normal distribution was only an ideal distribution. Actually non-normal signals were more common. For Non-normal signal, the second-order statistics was only part of the signal. Higher-order statistics were considered to achieve more information. Statistics those were higher than second-order call higher-order statistics. High-order statistics were the main analytical tools for Non-minimum phase, non-causal, non-normal signals and also use widely in many fields.

High-order statistics can be expressed in formula (4) and (5):

$$\mathrm{m}_4 = \frac{MN}{mn}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}(I_t(m,n)-\mu)^4 \tag{4}$$

$$E_{mn} = \frac{MN}{mn}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} I_t(m,n)^2 \tag{5}$$

In formula (4) and (5), m_4 was the fourth-order central moment of image, E_{mn} was the energy of image segmentation.

This chapter used the combination of low-order statistics and higher-order statistics to extract the background quickly and accurately.

B. Determine the image segmentation method.

Vehicle detection was based on the virtual loops so that the image segmentations were determined by virtual laying loop. The area of image segmentation should be selected for image requirements.

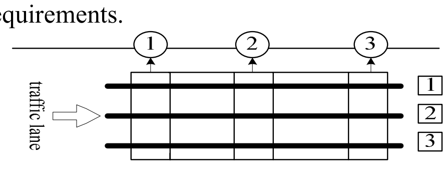


Fig.1 the Manner of Laying Loop

In Fig.1, ①、②、③were three detection loops, $\boxed{1}$、$\boxed{2}$、$\boxed{3}$ were three vertical detection lines. From the manner of laying loop in Fig.1, a segmentation mode can be achieved based on the second detection line. It was showed in Fig.2:

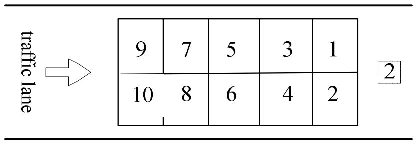


Fig.2 the Manner of Segmentation

C. Extract background

After determining the number of image segmentation, then extract background by similar judgment blocks and form a new background using the block in order. The flow chart was shown in Figure 3.

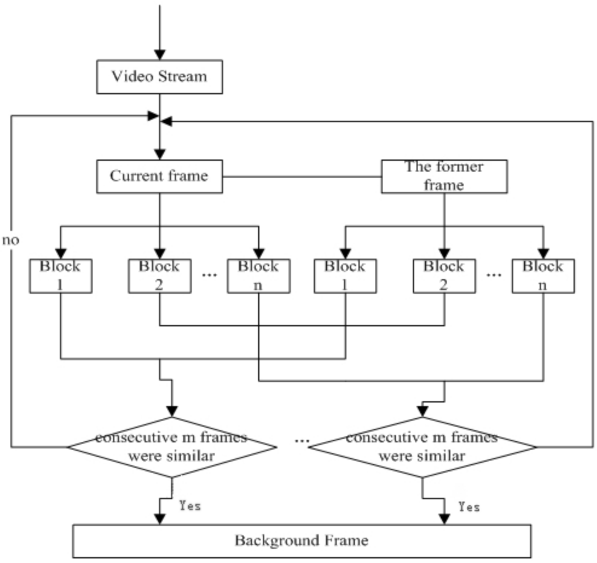


Fig.3 the Flow Chart of Background Extraction

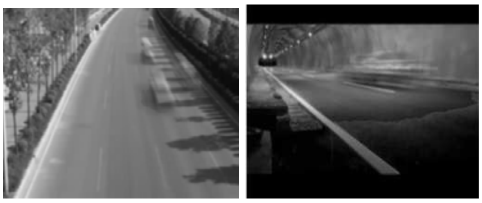
In Fig.3, make a comparison of the feature of continuous frames among video stream. If the features of m frames image remain the same, then the last frame was the background image

III. EXPERIMENTAL RESULTS AND DISCUSSION

To test the effect of background extraction based on invariance, using a section of urban freeway and tunnel surveillance video to make a comparison of this method and other background extraction methods, which was shown in Fig.4. Where Figure (a) was for the urban expressway images, Figure (b) was for the tunnel image.

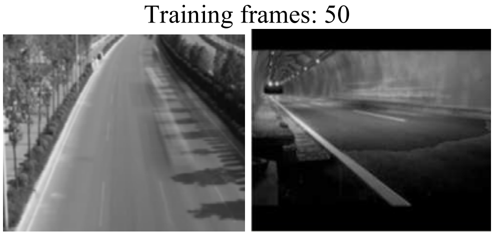
(a) Urban expressway (b) tunnel

Fig.4 Original Image



(a) Urban expressway (b) tunnel

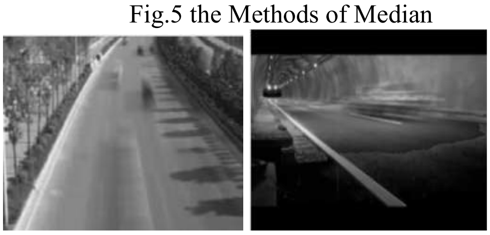
Training frames: 50



(a) Urban expressway (b) tunnel

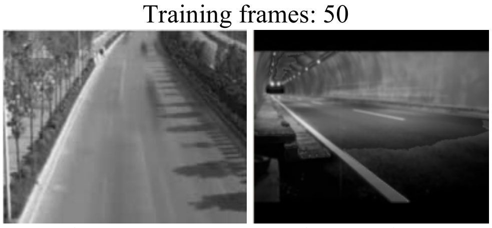
Training frames: 100

Fig.5 the Methods of Median



(a) Urban expressway (b) tunnel

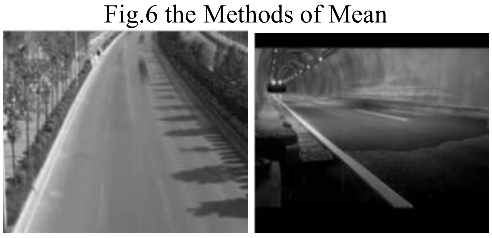
Training frames: 50



(a) Urban expressway (b) tunnel

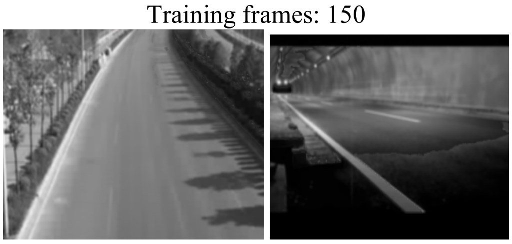
Training frames: 100

Fig.6 the Methods of Mean



(a) Urban expressway (b) tunnel

Training frames: 150



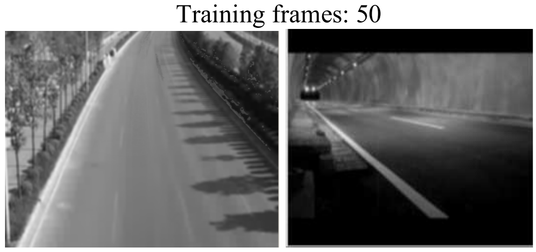
(a) Urban expressway (b) tunnel

Training frames: 300

Fig.7 the Methods of Mixture of Gaussians

(a) Urban expressway (b) tunnel

Training frames: 50



(a) Urban expressway (b) tunnel

Training frames: 100

Fig.8 the Methods of Segmentation

Figure 5 to 8 were respectively effects of the methods of Median, Mean, Mixture of Gaussians, and Segmentation. It can be seen from the figure that the effects of background extraction was not very satisfactory for methods of Median and Mean with fewer number of frames. The methods of Mixture of Gaussians extracted a better background, but the model was complex and needed a number of frames. It was difficult for the actual situation. Segmentation based on the invariance could get a ideal background with less frames. As Table 1 showed, Segmentation needed the least number of frames and time-consuming in the context of getting a good background.

Tab.1 the Comparison of Background Extraction methods

Parameters	*Median*	*Mean*	*MOG*	*Segmentation*
Frames(frame)	300	280	350	120
Time(s)	12	10.4	20	4.6

In natural environment, background extraction should be updated with circumstances change owing to changing lighting conditions. So the update background in real-time video detection was an important and complicated task[11-18]. Use Segmentation to update blocks with regard to the limitation of the change scope of the road background. That is, when a new background block was detected, new background block replaced the corresponding block, which was shown in Fig.9. Fig.10 was the background for the current frame.

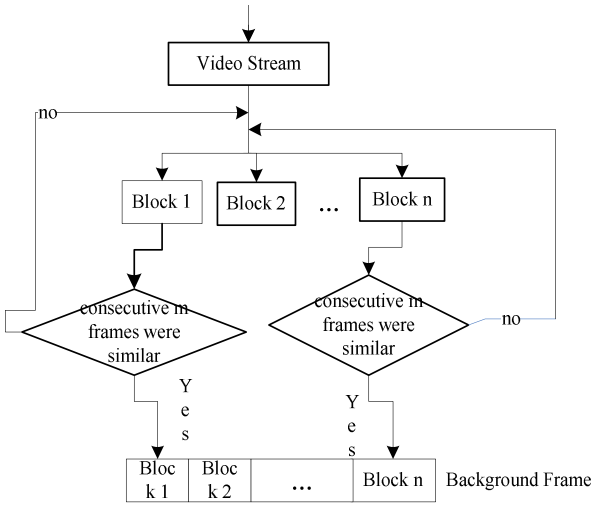
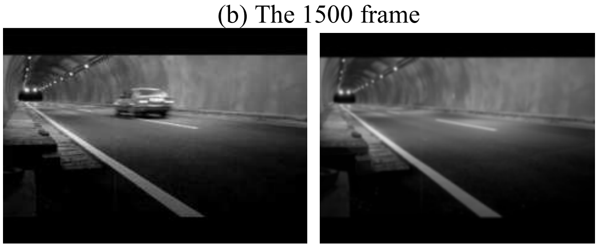


Fig.9 the Flow Chart of Background Updating

(a) The 1250 frame

(b) The 1500 frame



(c) The 2100 frame

Fig.10 the Result of Background Updating

This Background Updating method could fully meet the demand of accuracy and real-time from Fig.10.

IV. CONCLUSION

According to the experiment, Segmentation based on the invariance algorithm was with Small amount of computation, adapted to background changes among these background extraction and adaptive algorithms. It was more flexible and target, and improved the accuracy and real-time of the results of background extraction.

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