Moving Object Detection Based on Running Average Background and Temporal Difference

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***Abstract*—In order to detect moving objects from video sequences with complex background, we propose an algorithm which is based on running average background modeling and temporal difference method. Firstly, we utilize the running average method to dynamically updating the background image. Through using background subtraction, we get a foreground image. Secondly, we use temporal difference method to get a difference image. By combining the foreground image with the difference image, the common information between them can be achieved. Finally, we eliminate the noise in the combined image by using the median filter, and then we can get the moving objects. Experimental results show that, comparing with traditional running average method, temporal difference method and Gaussian mixture background modeling method, our method can detect the moving objects from complex backgrounds more accurately with low computational complexity.**

Keywords-running average; temporal difference; gaussian mixtrue model; moving object detection.

I. INTRODUCTION

Moving object detection in video stream is the essential step of intelligence visual surveillance application. And it is also an important research topic in the field of gait recognition, behavior recognition, etc. In most surveillance area, the scene always changes dynamically, this result in the difficulty of object detection. Although a lot of studies have been proposed in recent years, the subject is still challenging.

The difficulty of moving object detection is mainly caused by the changing scenes, the moving objects may become a part of the scene when they come to a stop, meanwhile, the scene maybe affected by the illumination changing, camera shaking, leaves swaying, etc.

In recent years, many moving object detection algorithms have been proposed, they involve background subtraction, temporal difference, optical flow, and so on. Between these algorithms, the most widely used one is the background subtraction. Background subtraction algorithm can be divided into running average background, Gaussian mixture background, kernel density background, eigen-background according to the background models [1-4]. However these background models have the problem of high computational complexity except the running average background model. The running average background costs low computational complexity but has some troubles selecting the model updating rate. If the updating rate is too high, it may cause artificial "tails" to be formed behind the moving objects [5].

In order to overcome the existing problem in the traditional running average background model, we propose an algorithm to combine the running average background with the temporal difference method. Our proposed method solves the updating rate selection problem, improves the detect result, and keeps low computational complexity.

II. RUNNING AVERAGE BACKGOUND

Running average background model dynamically update the background image to adapt to the scene changing by using the weighed sum of the current image and background image. The updating formula is:

$$B_{t+1}(x, y) = (1 - \alpha)B_t(x, y) + \alpha F_t(x, y) \tag{1}$$

Where α is the updating rate, B_t is the background image at the time t, F_t is the current image at time t.

The updating rate α represents the speed of new changes in the scene updated to the background frame [5]. However, α cannot be too large because it may cause artificial "tails" to be formed behind the moving objects [6].

Because the running average background just needs to compute the weighted sum of two images, so it has low computational complexity and space complexity. Dynamically updating the background makes this model can adapt to very complex scene.

III. TEMPORAL DIFFERENCE

Temporal difference method computes the difference image between two consecutive frames [7], then, after thresholding the difference image, we can get the moving objects. This method has low computational complexity, however, it is very sensitive to the threshold, too small threshold will cause a lot of noise in the detected results, but if the threshold is too large, much information of the objects will be missing. Temporal difference method is also affected by the speed of the moving objects, if the objects move too fast, using temporal difference will result in treating one object as two.

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IV. OUR PROPOSED METHOD

Running average background has the advantage of low computational and space complexity, but has some troubles in selecting the updating rate α .

The traditional running average background using the weighted sum to update every pixel in the background image, however it is not reasonable to do so, because it will introduce the moving pixel in the current image into the background, then the background will be polluted by pixel logically not belonging to it.

So, we use the selectivity running average background model to dynamically update the background image. The updating formula is as follows:

$$\begin{cases} B_{t+1}(x,y) = \alpha F_t(x,y) + (1-\alpha) B_t(x,y) \text{ if } F_t(x,y) \text{ is background} \\ B_{t+1}(x,y) = B_t(x,y) \text{ if } F_t(x,y) \text{ is foregound pixel} \end{cases} \quad (2)$$

However, the selectivity running average model still has the updating rate selection problem.

We introduce the temporal difference method into the selectivity running average background model to improve the accuracy of the detected results.

The figure 1 shows the processing steps of our proposed method. We select a small updating rate to update the background, and use the current image to subtract the background to get the foreground image. We thresholding foreground image by using a large threshold. The objects in the foreground image may have drop shadow because the background updates too slow. However, there is only little noise, and the most information of the objects is preserved.

We use the temporal difference method to get the difference image, and thresholding it by using a very small threshold. The difference image may contain a lot of noise, because of the small threshold, but the contours of the moving objects have been preserved very well.

Then, we combine the foreground image with the difference image through the “Logical AND” operation between the two binary images. By doing the “Logical AND” operation, we eliminate a lot if noise in the difference image, and also eliminate the drop shadow in the foreground image.

V. POST-PROCESSING

The result image which is from the “Logical AND” operation between the foreground image and the background contains little salt and pepper noise. As we know, the median filter can remove the salt and pepper noise very well, so we utilize the median filter to post-process our detect results.

For every pixel in the result image, we represent the original gray-level by the median gray-level of its 3 × 3 neighbor.

$$\hat{f}(x,y) = \underset{(s,t)\in S_{xy}}{median}\{g(s,t)\} \quad (3)$$

Where S_{xy} is the neighbor of the pixels.

After the median filter post-processing, the noise can be removed, and moving objects can be detected.

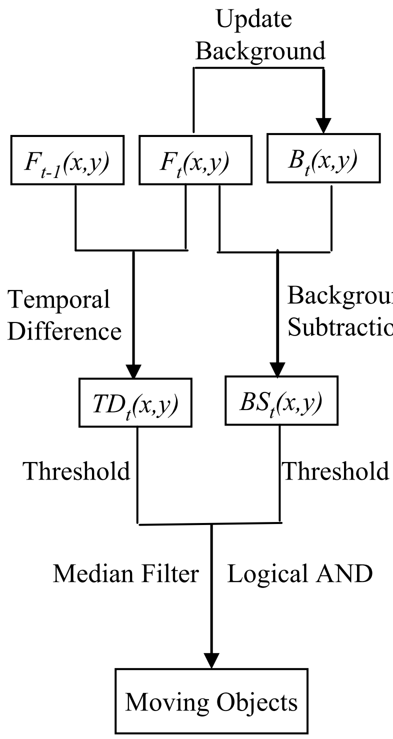

Figure 1. The framework of our method

VI. EXPERIMENTAL RESULTS AND ANALYSIS

On a common personal computer, we using the Microsoft’s Visual C++ 6.0 Integrated Development Environment and the Intel’s Open Source Computer Vision Library to implement our proposed method, traditional running average background method, temporal difference method, and Gaussian mixture model. We select two standard video sequences to test the algorithms. We only did simple post-processing on each sequence to remove the most noise in the result images. In order to see more clearly of the objects, we using red color to draw the moving object on the original image.

The figure2 shows the result images, and table1 shows the average detect time of each algorithm to detect one frame.

From the experiment result, we can clearly see drop shadow behind the moving objects in the result images which are detected by using traditional running average background algorithm.

The objects detected by temporal difference method have too less information, we can find there is a person not be detected in sequence 2.

The result images detected by Gaussian Mixture Model contains a lot of noise, and we can’t even distinguish moving objects from noise. The reason is that Gaussian Mixture Model is very sensitive to sudden illumination changing [8,9,10], and the intensity of the coming car is too high, it results in sudden illumination changing of the whole scene.

Our method doesn't have such problems, and can detect moving objects better. From table1, we can see the computational complexity of our method is very low.

TABLE I. COMPUTATIONAL COMPLEXITY(MS/FRAME)

Algorithms	Computational Complexity	
	Sequence1	*Sequence2*
Running Avergae	41.94[a]	6.55
Temporal Difference	33.65	5.38
Gaussian Mixture Model	188.80	40.07
Our Method	44.87	7.63

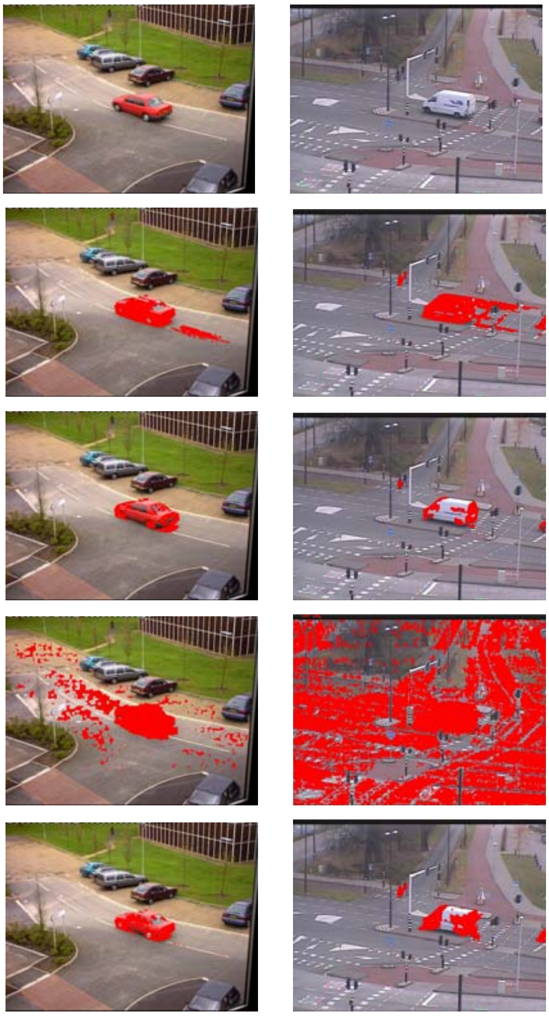

Figure 2. Result Imgaes
The first row is the original image, the second row is detected by traditional running average method, the third row is detected by temporal difference, the forth row is detected by Gaussian mixture model, and the last row is detected by our method. The image in the first column is 768×576, and the image in the second column is 352×288.

VII. CONCLUSION

This paper proposes a moving object detection algorithm which combines the running average background method and temporal difference method. Through taking the advantage of each method's strong points, our method can get good detect result and keeps low computational complexity.

Our method can deal with slow slighting changes by slowly updating the background. It also deals with swaying branches, and can be applied to real time surveillance systems. However, this method still has some disadvantages, it may divide a large moving object into several parts, that is a problem, but we can solve it by dilate operation or morphology operation.

In the future research work, we will focus on designing a more robust moving object detection algorithm, and integrate it into an embedded surveillance application system.

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