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A new moving target detection algorithm

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Abstract: The traditional GMM can easily detect the background as a moving target and is sensitive to the illumination changes. So this paper put forward a moving target detection algorithm combining the improved custom GMM with the five-frame interframe difference method. After the video image sequence is preprocessed, the GMM is added with the balance coefficient and the merged useless Gaussian distribution is combined. Then the improved GMM is combined with the five-frame interframe difference method to obtain the detected target. Simulation experiments show that the improved algorithm adapt the environment better. The improved algorithm reduces the impact of illumination changes on moving target detection, and significantly reduces the false detection rate.

1. Introduction

Moving object detection is the separation of moving objects from the background[1]. The current classic algorithms for moving target detection are: optical flow method, interframe difference method and background division method[2]. The difference method is proposed the moving target by the difference of the pixel values between two consecutive frames or multiple frames. The background update is not needed, and the algorithm is relatively simple, but the moving target is incomplete. Based on the research and analysis of the above target detection algorithm, this paper proposes a new type of target detection algorithm, which adds the balance coefficient and the unusable Gaussian distribution to the traditional GMM to improve the adaptability of the algorithm to the scene change, and the five-frame difference algorithm. A logical or combined operation is performed such that the effect of illumination is reduced when performing target detection.

2.Gaussian mixture algorithm and improved

2.1 GMM model initialization

The probability density function defining the current pixel is the weighted sum of the K Gaussian model probability density functions P（X_i）:

$$P(X_i) = \sum_{i=1}^{K} w_{i,t} G_i(X_t, \mu_{i,t}, \sigma_{i,t}) \quad (1)$$

In the middle, $w_{i,t}$ is the weight of the I probability density function at time t. G_i represents the I Gaussian distribution. X_t means the pixel value of the current observation point. $\mu_{i,t}$ means the mean value of the I probability density function. $\sigma_{i,t}$ expresses as the covariance of the i probability density function. N means the dimension of X_t.

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2.2 Foreground target extraction

Match the pixels of the model background, and if it is not satisfied, it will be the target pixel. The matrix using the first B distributions to represent the background:

$$B = \arg min_b \left(\sum_{i-1}^{b} w_{i,t} > T\right) \quad (2)$$

T represents the minimum weight ratio required to form the background. When T takes a small value, only indicate one Gaussian distribution, when T takes a large value, indicate multiple descriptions. If at least one of the distributions matches the pixel, the pixel is the background point, otherwise it is the front point, and the pixel segmentation is completed.

2.3 Parameter update

When at least one Gaussian distribution matches, the mean $\mu_{i,t}$ and the covariance matrix $\sigma_{i,t}$ of the mismatched Gaussian distribution doesn't need change. The Gaussian distribution starts updating:

$$\mu_{i,j} = (1-\rho)\cdot\mu_{i,j} + \rho\cdot X_t \quad (3)$$

2.4 Improvement of GMM

When detecting the moving target, the K value in the traditional GMM is determined to be constant, which hinders the adaptability of the algorithm. When there is no moving object in the video scene, it does not need too much Gaussian distribution to occupy the computing resources, and when the target appears in the video scene, the pixel value to be calculated will increase significantly, and then multiple distributions are used for calculation. So, this paper proposed a new opinion to use K value to make adaptive adjustment to GMM. The specific steps are as follows:

By adding a control modulus δ to keep weights and covariance be reasonable

$$\sigma_{i,t} = (1+\delta)\sigma_{i+1,t} \quad (4)$$

$$w_{i,t} = (1-\delta)w_{i+1,t} \quad (5)$$

Invalid Gaussian distribution when the K value reaches the maximum. When the two Gaussian distributions of the same pixel are smaller than the threshold, the two Gaussian distributions are combined and the parameters are updated:

$$w_{k,t} = w_{i,t} + w_{j,t} \quad (6)$$

$$\mu_{k,t} = \frac{w_{i,t}\mu_{i,t}+w_{j,t}\mu_{j,t}}{w_{i,t}+w_{j,t}} \quad (7)$$

$$\sigma_{k,\ t} = \frac{w_{i,t}\sigma_{i,t}+w_{j,t}\sigma_{j,t}}{w_{i,t}+w_{j,t}} \quad (8)$$

Updated parameters can combine useless Gaussian distributions to make the GMM more adaptive to the scene.

3. Five frame difference algorithm

The five frame difference method is to be taken continuous five-frame image. After image preprocessing, using one perform a two-two difference with the remaining four frames. Then can get the differential image. Through appropriate thresholds divide the difference image to obtain a second difference image after the difference. After using logical AND operation of the binarization image, received $m_1(x,y)$ and $m_2(x,y)$.Then using the result by logically OR to get the target area m（x,y）:

$$m(x,y) = m_1(x,y) \cap m_2(x,y) \quad (9)$$

4.The flow of improved new algorithm

Firstly, the sequence frame of the video image is read for simple image processing, and then the image sequence is subjected to five-frame difference and the GMM improved by adaptive model updating is combined by using logical "or" operation to obtain the moving target, and then obtained. The gait target is further processed in order to obtain a clear and complete moving target. The detailed flow chart of the algorithm in this paper is shown in Figure 1:

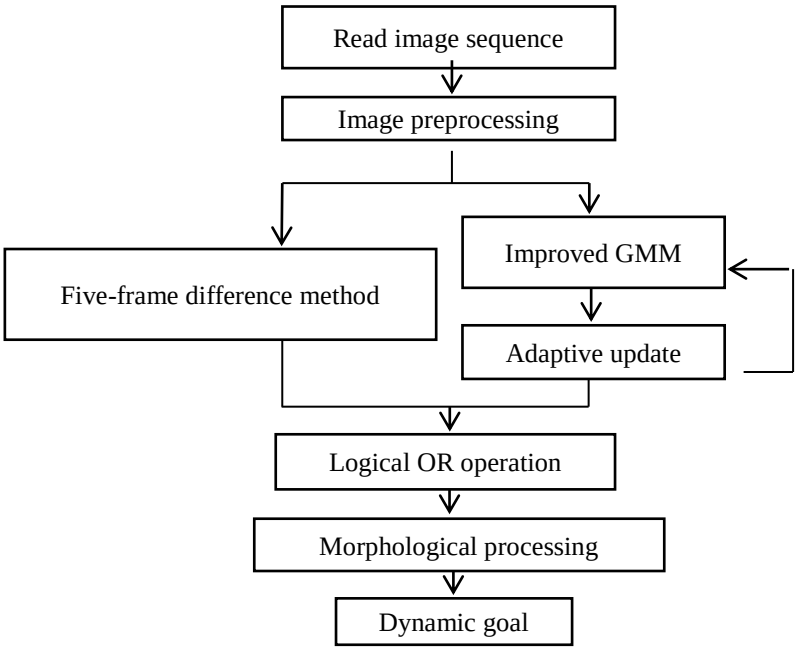


Figure 1. Algorithm flowchart

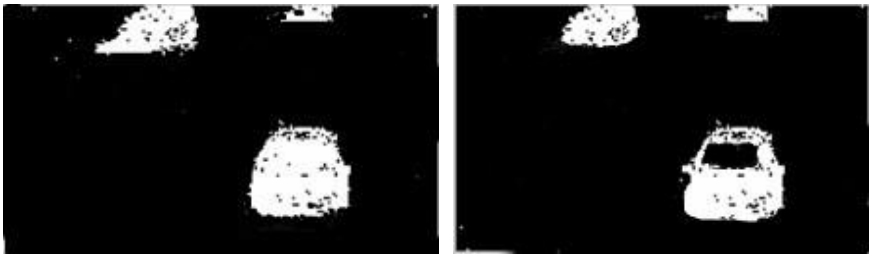
5.Experimental results and analysis

5.1 Simulation experiment results

This paper uses the software MATLAB R2014b for experimental simulation on the PC hardware platform with parameters of Intel Core I5-3337U and CPU2.7GHz. In order to verify the validity and practicability of the algorithm, I tested the algorithm under two conditions: illumination equalization and obvious illumination changes. At the same time, the experimental results are compared with the traditional GMM and the traditional difference algorithm.

Figure 2 shows that the results of various scenes detected by the car passing through the scene without significant changes in outdoor lighting. It can be observed from Figure 2 (b) that the traditional GMM can detect the contour of the moving target but the cavity phenomenon is more obvious; as shown in Figure 2 (c), it can be observed that the traditional interframe difference method is more affected by noise, and the contour is not obvious. Figure 2(d) observes that the improved algorithm proposed in this paper extracts the contour of the target more accurately and achieves a good target detection effect.


（a）Processed image （b）Traditional GMM

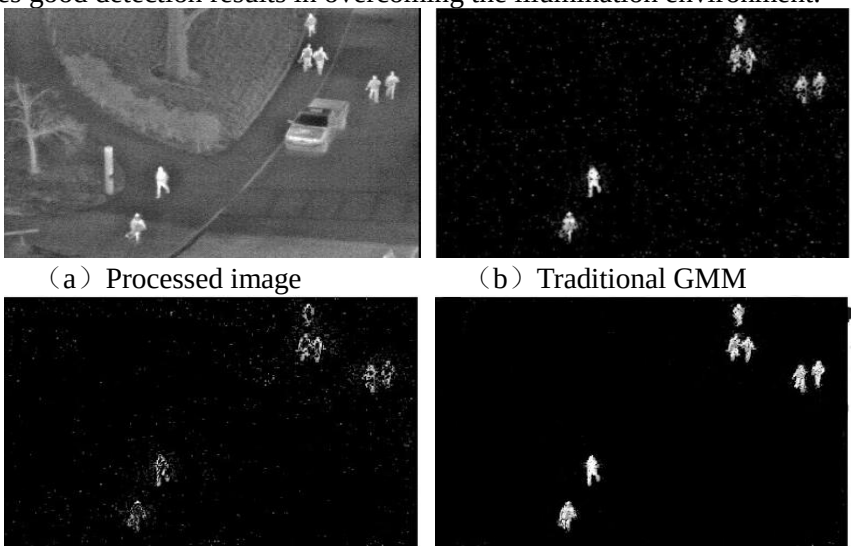


（c）Traditional difference method （d）New algorithm

Figure 2. Test results in outdoor light balance

Figure 3 shows the results of each algorithm in the case where pedestrians have obvious changes in outdoor lighting. It can be observed from Figure 3 (b) that the traditional GMM can detect the contour of the pedestrian but the cavity phenomenon is obvious; as shown in Figure 3 (c), the contour of the traditional difference method is not clear; Figure 3(d) observes this paper. The proposed improved algorithm extracts the contour of the target more accurately and achieves a good target detection effect.

It can be seen from the test results that the motion target contour is clearer and clearer in the case of sudden illumination, and the noise is also significantly reduced, which indicates that the proposed algorithm achieves good detection results in overcoming the illumination environment.



（a）Processed image （b）Traditional GMM

（c）Traditional difference method （d）New algorithm

Figure 3. Test results under changes in outdoor lighting

5.2 Result analysis

The evaluation of the practicability and effectiveness of the algorithm generally depends on the recognition rate R_{RE} and the false positive rate R_{FAR}.

$$R_{RE} = \frac{T_P}{T_P \cdot F_P} \tag{10}$$

$$R_{FAR} = \frac{T_P}{T_P \cdot F_n} \tag{11}$$

Among them, T_P is the number of pixels that correctly detect the foreground target, F_P is the number of pixels that are not correctly detected, and F_n is the number of pixels that incorrectly detects the target as the background. The high recognition rate of an algorithm indicates that the accuracy of the algorithm is good, and the low false detection rate of an algorithm indicates that the algorithm has excellent performance.

In order to reflect the superiority of the improved algorithm in this paper clearly and intuitively, I selected 30 frames to calculate the unrecognized rate and false detection rate by differently using the

improved algorithm, traditional GMM and interframe difference method. The results are shown in Table 1. It can be observed from Table 1 that the proposed algorithm has significant superiority in both recognition rate and false detection rate compared with the other two algorithms.

Table 1. Identification rate and false detection rate of three algorithms

Algorithm	R_{RE} **(%)**	R_{FAR} **(%)**
Traditional GMM	82.3	13.7
Traditional difference method	85.6	7.2
New algorithm	92.7	3.2

At the same time, the three algorithms are compared in terms of time-consuming and algorithmic complexity. The processing time of each algorithm is counted for 60 frames of the same video, as shown in Table 2. It can be seen from the table that the traditional GMM is time-consuming due to background modeling. Although the processing speed of the traditional inter-frame difference method is fast and the effect is poor, this paper proposes that the processing time of the improved calculation is higher than the difference method, but the operation speed is still better than that of the GMM.

Table 2. Average processing time in per frame for the three algorithms

Algorithm	**Light balance (ms)**	**Light change (ms)**
Traditional GMM	303	467
Traditional difference method	57	69
New algorithm	213	302

6.Conclusion

In this paper, an improved algorithm based on GMM and inter-frame difference is proposed. The adaptability of the algorithm about scene changes is improved by adding equilibrium coefficients to GMM and merging useless Gauss distribution. Then the improved algorithm and five-frame difference method are combined by logic or operation to get the algorithm in this paper. The effect of illumination is reduced when performing target detection. Although the algorithm complexity is higher than the difference between frames, it can better obtain clear and complete moving targets, and overcome the influence of illumination changes on target detection. However, the algorithm in this paper still has some shortcomings. In the case of excessive interference, the moving target cannot be extracted well.

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