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A Moving Objects Detection Method with Resistance to Illumination Change

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Abstract

Moving objects detection is conducted in the sequential image of moving objects, which is favorable to detect, identify and analyze the moving objects. It has been applied in video surveillance, virtual reality, and advanced user interfaces. Based on existing research on the Frame Difference Method (FDM) and the Background Subtraction Method (BSM), considering the short time interval between adjacent images used for difference, FDM is adopted for its smaller impact by scene illumination variation, which is complementary to the drawback that BSM is sensitive to environmental variation; while BSM can detect the integral moving objects, which can also make up the disadvantage of FDM in failing to detect the integral moving objects. In this paper, we propose a moving objects detection method with resistance to illumination change. We conclude from the experiment that this method is noise-proof and can adapt the abrupt change in illumination to ensure accuracy of the detection.

Keywords: *moving object detection, video surveillance, FDM, BSM, illumination change*

1. Introduction

With the development of society and people's increasing awareness of security, video surveillance has been widely used in many fields like transportation monitoring, community management and campus management. Parts of the main objectives of video surveillance are moving objects detection and tracking, which are closely related to each other. Moving objects detection, as the primary step in video surveillance, will directly influence the tracking, identifying and analyzing of moving objects. There is a variety of variables influencing the tracking of moving objects like the background variation, sudden change of illumination in monitoring environment, shadow and noise, which makes it more difficult to detect the moving objects [1]. Over recent years, scholars both inland and abroad have been looking for the right approach to detect the moving objects in video sequences and have already made some progress. Methods already put forward include the optical flow method which usually uses characteristics of flow-vectors over tome to indicate moving regions in a video sequence [2]; Frame Difference Method (FDM) that finds objects by using the difference between the images of the current frame and previous or next frame within the successive frames [3] and Background Subtraction Method (BSM) that uses the difference between the initial background image, when any objects are not tracked and the frame image when objects are moving [4]. A. Doshi and A. G. Bors [2] introduced the optical flow method to detect moving objects. However, most calculating using the optical method is too complicate, and also costs more time and memory. Without the support of special hardware, this method can not be applied to the real-time system. FDM has three advantages: simple calculation, small amount of computation and easy to implement. But it is inaccurate in the detection zone, as using the previous or next frame from the current frame represents the background image of the current frame [5]. Out of these three categories, BSM received the most attention due to its computationally affordable implementation and its accurate detection of moving entities. While BSM is highly dependent on a good background model to reduce the influence of these changes in the surveillance environment due to noise and lighting, etc [6].

In addition, there are also some methods in moving target detection. These methods may be a signle method, such as space-time model, hybird graph method and feature weight, or a combination of two methods. A method based on Horizontal Edges with Local Auto

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Correlation (LAC) was used to detect vehicles[7]. It does not use the vertical edge. Mengxin Li and Jingjiang Fan propose a methond ,which combines the inter-frame difference method with improved background subtraction methond [8]. The improved background subtraction method of the method makes use of LBP to build the background. But the background can not be updated real-time.

Given the above analysis, the paper proposes a method that is not only accurate in the detection zone, but also robust to noise and sudden illumination changes. The remainder of the paper is organized as follows: Section 2 describes our approach in detail. In Section 3, we present the experimental results and discussion. Finally, our conclusion and acknowledgment are provided in Section 4.

2. Proposed Method

In order to solve the problem that results from scene illumination variation, we propose a novel approach, which combines the asymmetric frame difference method (AFDM) with the adaptive mixture of Gaussians method (AMoGM). First, it is the detection results that only use the AFDM, then we show the results only using AMoGM and give the detection results come from the proposed method. The algorithm flow chart is shown in Figure 1.

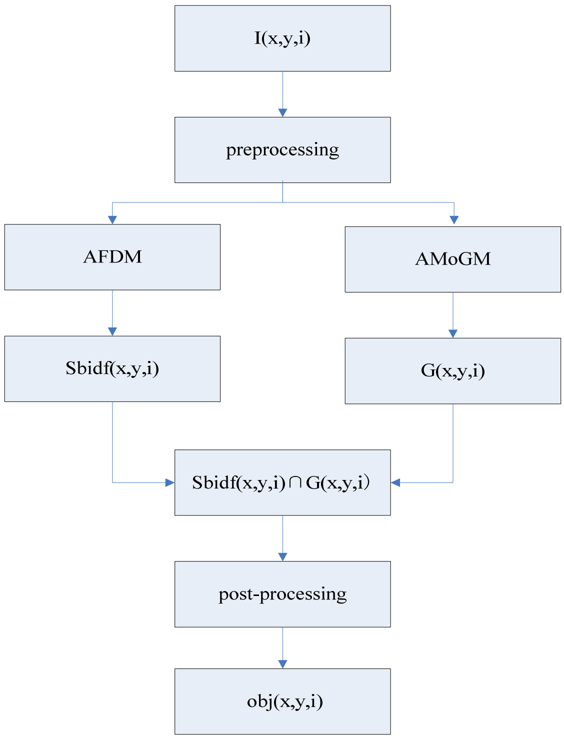

Figure 1. The Flow Chart of the Proposed Method

2.1. Image Preprocessing

To avoid visible strip with distortion, easily programmed and saving memory consumption, the input color image should be converted into a grayscale image in accordance with the formula (1). Each pixel with eight nonlinear scales saved and there are a total of 256 gray levels [9].

$$Gray = 0.299 \times R + 0.587 \times G + 0.114 \times B \quad (1)$$

The processes of the images generated and transmitted are often interfered by the noise, which is mainly due to camera shake, image digitalization and light jitter, etc. At the same time FDM is sensitive to noise that affects the accuracy of target detection, so it is necessary for the images to denoise. Median filter by selecting a shape of the active window, such as rectangular, linear, approximately circular or cruciform, etc, which contains an odd number of pixels is an effective suppression of image noise technology. Supposing W represents a sample window, the pixel value will be got by the formula (2):

$$I(x,y) = med[I(x-k,y-l),(k,l) \in W] \quad (2)$$

To improve the visual effect of the image, highlight the interesting course and facilitate subsequent analysis and processing, the image enhancement process will be implemented to the denoised video image, whose quality has been degradated. This paper selects the histogram equalization to enhance the image. The gray histogram will be evenly distributed in the entire gradation range from a relatively concentrated gradation interval. By increasing the dynamic range of the pixel gray we achieve the overall image contrast.

2.2. AFDM

FDM is a method that compares between the adjacent frames corresponding points of pixel values to find moving targets: the scene without moving target, the change of the adjacent frames corresponding points of pixel values is very small; conversely there will be more obvious changes. Related to the symmetrical frame difference method [10], AFDM can avoid to reuse of the current frame which has been destructed or polluted to bring about the error detection. $I(x,y,i)$ is the pixel value of the ith frame at the coordinate of (x,y), the corresponding points of the pixel values in the previous frame and next frame are respectively expressed as $I(x,y,i-1)$ and $I(x,y,i+1)$. $bidf(x,y,i-1,i)$ is a binary difference image between $I(x,y,i-1)$ and $I(x,y,i)$, $bidf(x,y,i-1,i+1)$ is a binary difference image between $I(x,y,i-1)$ and $I(x,y,i+1)$, therefore the dissymmetric difference operation of the ith frame is expressed as follows:

$$bifd(x,y,i-1,i) = I(x,y,i) - I(x,y,i-1) \quad (3)$$

$$bidf(x,y,i,i+1) = I(x,y,i+1) - I(x,y,i-1) \quad (4)$$

$$sbidf(x,y,i) = bidf(x,y,i-1,i) \bigcap bidf(x,y,i,i+1) \quad (5)$$

The formula (3) shows that only $bidf(x,y,i-1,i) = 1$ and $bidf(x,y,i-1,i+1) = 1$ at the same time, then $sbidf(x,y,i) = 1$. It can eliminate the revealed background image, and access to the moving objects region of the ith frame.

2.3. AmoGM

BSM is a basic method of object detection and tracking, which uses a reference image as a background model, calculates the difference image of the current frame and the reference image then uses the threshold separating out moving targets. The reconstruction and updating of the background model directly determine the detection results. Based on the Muti-modal mixture of Gaussian background difference method [11, 12], simultaneously uses K uncorrelated Gaussian distributions to describe the state of a pixel, $K \in [3,7]$. K is 4 in this article. Each Gaussian distribution has its own mean, variance and weight. In the detection process, as long as the pixel value is in accordance with any one of the K Gaussian distributions which represent the background, then the pixel has the background characteristics and is considered as the background pixel; on the other hand, the pixel is determined as the object pixel.

The probability distribution of the estimated of the coordinate of (x,y) in the ith frame is expressed as the formula (4):

$$P(I(x,y,i)) = \sum_{k=1}^{K} \eta_{i,k,xy} * \varphi(I(x,y,i), \mu_{i,k,xy}, \sum{}_{i,k,xy}) \tag{6}$$

Where $\varphi(I(x,y,i) \mid \mu_{i,k,xy}, \sum{}_{i,k,xy})$ is the kth Gaussian distribution at the coordinate of (x,y) in the ith frame, which is defined as the formula (7).

$$\phi(I(x,y,i), \mu_{i,k,xy}, \sum{}_{i,k,xy}) = \frac{1}{(2\pi)^{n/2} \mid \sum{}_{i,k,xy} \mid^{1/2}} e^{-\frac{1}{2}(I(x,y,i)-\mu_{i,k,xy})^T \sum_i^{-1}(I(x,y,i)-\mu_{i,k,xy})} \tag{7}$$

In the formula (5), n is the dimensionality of $I(x,y,i)$, $\mu_{i,k,xy}$, $\sum{}_{i,k,xy}$ and $\eta_{i,k,xy}$ respectively represent mean, variance and weight of the kth Gaussian distribution in the ith frame .Furthermore, $\sum_{k=1}^{K} \eta_{i,k,xy}$ =1. Because the gray image is single-channel, n is one when using a mixture of Gaussian model for the gray image builds the background. When initialized, μ_{init} is equal with each pixel value of the first frame, $\sigma_{init}^2 = 900$ and $\eta_{init} = 0.005$. According to the established background model, for $I(x,y,i)$, if it meets the formula (8) with one of its K Gaussian distributions, $I(x,y,i)$ will be considered to match with the background model. And D is set based on experience in order to determine the similarity, $D \in [2.5, 3.5]$.

$$\mid I(x,y,i) - \mu_{i-1,k,xy} \mid \leq D * \sigma_{i-1,k,xy} \tag{8}$$

If $I(x,y,i)$ matches with background, then $\mu_{i,k,xy}$, $\sum{}_{i,k,xy}$ and $\eta_{i,k,xy}$ will be updated in accordance with the formula (9), (10), (11). It means the background model will also be updated. While if $I(x,y,i)$ matches with any one of its K Gaussian distributions, we think $I(x,y,i)$ has no effect on a single model and the parameters of each Gaussian distribution of the remain unchanged model.

$$\mu_{i,k,xy} = (1-\rho)\mu_{i-1,k,xy} + \rho I(x,y,i) \tag{9}$$

$$\sigma_{i,k,xy}^2 = (1-\rho)\sigma_{i-1,k,xy}^2 + \rho(I(x,y,i) - \mu_{i-1,k})^2 \tag{10}$$

$$\eta_{i,k,xy} = (1-\lambda)\eta_{i-1,k,xy} + \lambda \tag{11}$$

In formula (9) and (11), λ is a model learning factor, $\lambda \in [0,1]$ and the greater the value of λ the background update faster. In this paper, $\lambda = 1/numFrames$ when $numFrames \leq 200$, and $\lambda = 1/200$ when $numFrames > 200$. ρ is parameter update rate, $\rho = \lambda / \eta_{i,k,xy}$.

If $I(x,y,i)$ does not match with any one of its K Gaussian distributions, now its distribution will be considered a new distribution form and need to be added to its original model. After added, if the number of Gaussian distributions in the model is greater than K, firstly K Gaussian distributions in the model will be sorted according to the $\eta_{i,k,xy} / \sigma_{i,k,xy}^2$ descending order, then the distribution with the minimum $\eta_{i,k,xy} / \sigma_{i,k,xy}^2$ will be substituted with a the new Gaussian distribution form and $\mu_{new} = I(x,y,i)$, σ_{new}^2 =900 and σ_{new}^2 =0.005. After background model updated, $\sum_{k=1}^{K}\eta_{i,k,xy}$ may be not one. So $\eta_{i,k,xy}$ will be done the normalization processing in accordance with the Equation (12):

$$\eta^{'}_{i,k,xy} = \frac{\eta_{i,k,xy}}{\sum_{k=1}^{K}\eta_{i,k,xy}}, k = 1,2...K \tag{12}$$

On the Gaussian distribution of each pixel model having been sorted, if the cumulative probability of the bth state is greater than T_0 and b is the smallest, the pixel belongs to a background state, the rest of the state is determined as a foreground, the formula (13). Thus we obtain the detection result $G(x,y,i)$. But if the number of the target pixels in the ratio of the total number of pixels is greater than 0.85, we think that the surrounding illumination intensity has changed, and the Gaussian distribution with $\max(\eta_{i,k,xy})$ among K Gaussian distributions in each pixel model will be replaced by corresponding pixel's distribution in the current frame. Its mean is equal with the pixel value, variance is 900 and weight is $\max(\eta_{i,k,xy})$. This process ensures that the new distribution is a determined background and the accurate detection of the next frame image.

$$B = \arg\min_b (\sum_{k=1}^{b}\eta_k > T) \tag{13}$$

2.4. Integrated Extraction Moving Object

For the ith frame image $Sbidf(x,y,i)$ is the result from the process of 2.2.and $G(x,y,i)$ is from the process of 2.3, then integrated extraction moving object $obj(x,y,i)$ will be got by the formula (14):

$$obj(x,y,i) = Sbidf(x,y,i) \cup G(x,y,i) \tag{14}$$

The formula (14) shows that only $Sbidf(x,y,i) = 0$ and $G(x,y,i) = 0$ at the same time, then $obj(x,y,i) = 0$. The value of $Sbidf(x,y,i)$ depends on the following two cases: if the number of the target pixels in the ratio of the total number of pixels is greater than 0.85, we think that the surrounding illumination intensity has changed, then $Sbidf(x,y,i) = bifd(x,y,i)$; otherwise $Sbidf(x,y,i) = sbifd(x,y,i)$.

After said detection, within the objects area may be the presence of small voids and the external may exit discrete noise points, as well as the presence of the shadow. So the image post-processing operation on the integrated extraction moving object is therefore necessary to improve the final detection results. Post-processing of the image mainly refers to the mathematical morphology processing of the binary image obtained [13], whose basic idea is to use the structural elements having a certain shape to measure and extract the corresponding shape in the image, in order to achieve the purposes of the image analysis and recognition. The basic operations of mathematical morphology include: dilation, erosion, opening (erosion followed by dilation) and closing (dilation followed by erosion). Erosion operation can make a moving object boundary inward contraction and eliminate small and insignificant objects. Selecting large structural elements can make objects between small connectivity etched away. Closing operation can fill the holes in the area, the narrow fracture, fine Mu gully and contour of the gap. So in this paper, we firstly use a closing operation to fill tiny holes in the body, smooth the boundary of the object boundary ,then a erosion operation to eliminate some small objects caused due to noise and illumination changes, and thus obtain the final results of the object detection.

3. Experimental Results and Analysis

The above is the description of the algorithm proposed by this paper. Next, the algorithm is simulated in MATLAB, especially in the complex environment where illumination suddenly changes and we have carried on the results qualitative and quantitative to the experiment results. Figure 2 is the detection result before illumination changes in a complex environment, of which the first one is an original image. Figure 2(a) is obtained with the method of 2.2 result, Figure 2(b) is the binary image of the moving Object detection using only 2.3 said method, Figure 2 (c) is the algorithm proposed in this paper test result obtained. Figure 3 is the corresponding test results after illumination change, wherein the first one is the original image, Figure 3(a) is used only 2.2 said method result obtained Figure 3(b) is a binary image of the moving target detection using only 2.3 said method obtained and Figure 3(c) is the proposed algorithm test result.

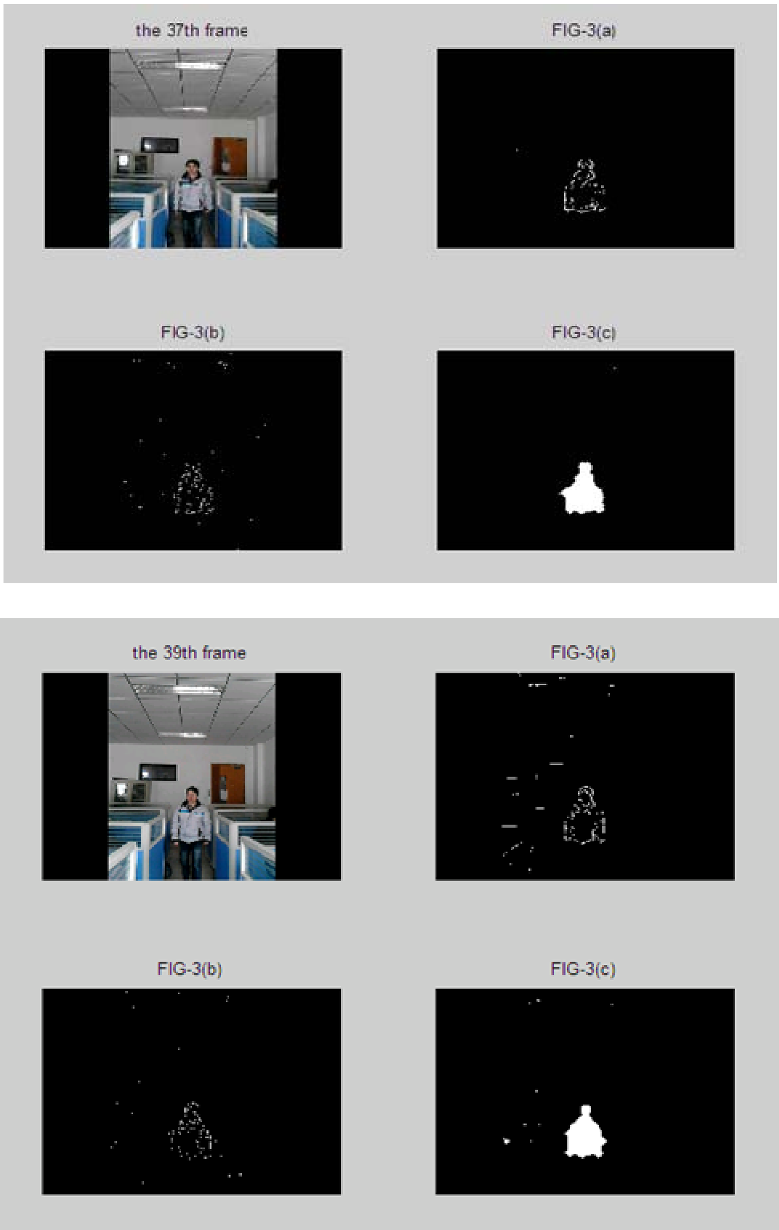

Figure 2. The Simulation Results before the Illumination Changes

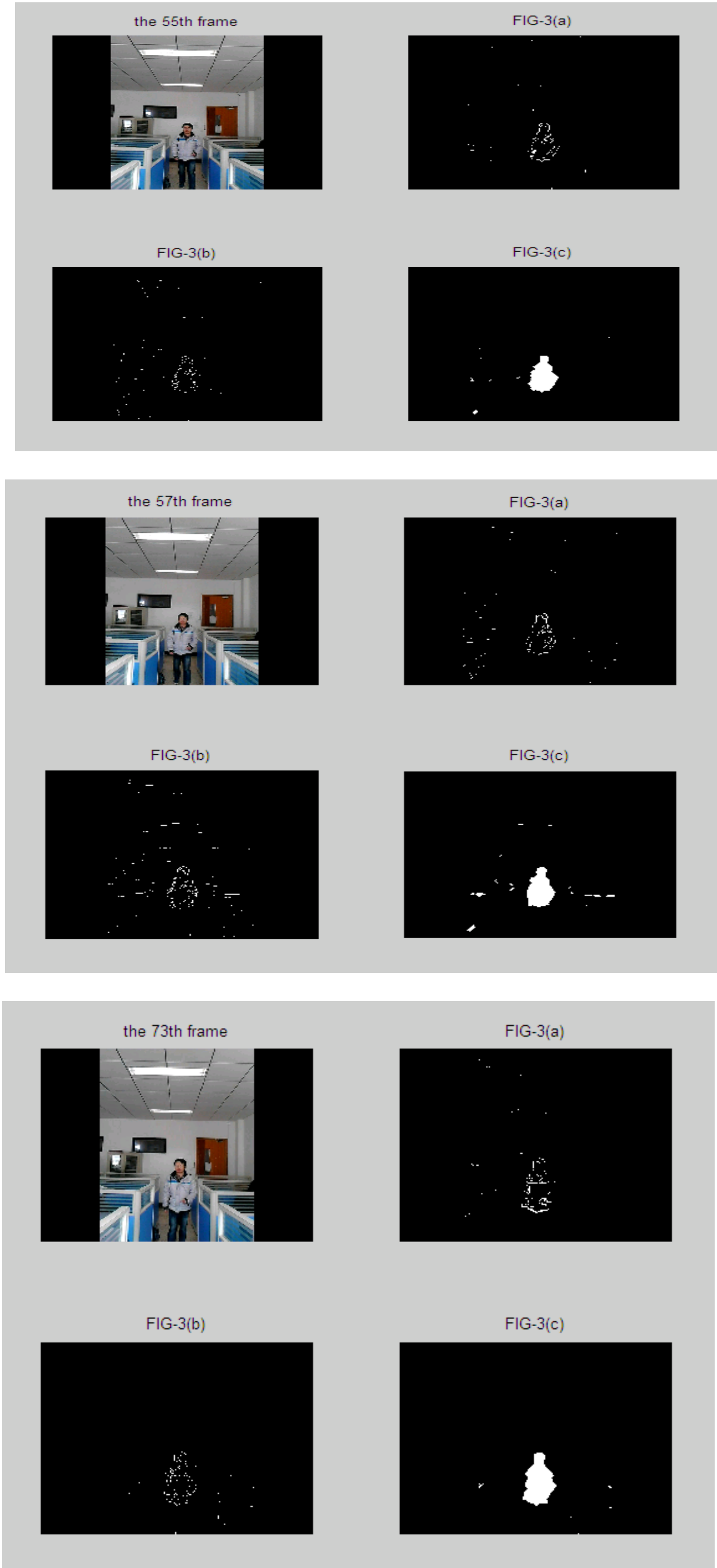

Figure 3. The Simulation Results after the Illumination Changes

Results from Figure 2 and Figure 3 and their contrast can be found that using only 2.2 said method, the extracted moving object boundary is not complete, and the target internal voids exist, but the robustness to environment change is relatively good. And just using 2.3 described method, the extracted moving target, although the outline of the moving target is more complete, is more sensitive to illumination change in the environment and the detection results are not ideal in the case of illumination mutation. During the moment of illumination changes, the probability of error detection increases and reconstructing each pixel's mixture Gaussian model will take some time. While using the proposed algorithm in this paper, the moving object boundaries intact, inner cavity is relatively small and has good robustness to illumination change, even in the case of illumination change also is able to detect the moving targets accurately. Due to the change in illumination, there are also detection errors, but the error is in a relatively small proportion, so the proposed method is still able to accurately detect moving objects. As time goes on, the impact of illumination variation is smaller and smaller, the false detection rate quickly returns to the allowed range, and the accuracy rate rebounds to the desired range.

According to the quantitative evaluation of the proposed method in [14], Recall and Precession are used to analyze the proposed algorithm:

$$\mathrm{Re}\,call = \frac{tp}{tp + fn} \tag{15}$$

$$\mathrm{Pr}\,ecision = \frac{tp}{tp + fp} \tag{16}$$

In the formula (15), tp represents the total number of true positive pixels, fn represents the total number of false negative pixels, and $(tp + fn)$ represents the total number of true positive pixels in the ground truth. In the formula (16), fp is the total number of false positive pixels, and $(tp + fp)$ indicates the total number of positive pixels in the detected binary objects mask.

Table 1 is obtained by 2.2, 2.3 and the algorithm of Precision and Recall, from which we can see that either before or after the light changes, the proposed algorithm has been improved more than 2.2 and 2.3. Although due to illumination variation, Recall and Precision decrease, the proposed algorithm is more reliable than 2.2 and 2.3, and is able to meet the requirements of accurate detection of moving objects.

Table 1. Precision and Recall of Algorithm

Algorithm	Illumination change	FrameNum	Precision	Recall
AFDM	Before	400	85%	82%
	After	400	83%	80%
AmoGM	Before	400	90%	87%
	After	400	80%	87%
Proposed	Before	400	94%	95%
	After	400	93%	90%

4. Conclusion

After full analysis of FDM and BDM, this paper proposes to combine AFDM and AMoGM to detect the moving objects. The proposed method not only compensates for the shortcomings that AFDM can't extract the complete moving object boundary, but also improves AMoGM robustness against illumination changes. Through the experiment results it can be seen that the algorithm can extract a complete moving target and the robustness to noise interference is also very good, even in the case of the ambient illumination changes. However, due to changes in illumination, moving objects is always with shadow, which brings interference for moving target detection. Therefore, using the algorithm of target detection process, it remains to be added the shadow processing, so as to improve the accuracy of the moving target detection

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